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Application of Neural Network-Support Vector Technique to Forecast U.S. Unemployment Rate

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ABSTRACT

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This research utilized five economic factors; 1) Consumer Price Index, 2) Return on Treasury Securities, 3) Total Nonfarm payroll, 4) Jobless Claims Filed, and 5) Stand & Poor 500 index to predict US unemployment rate. Historical time series data was obtained from the Economic Research web site of the Federal Reserve Bank of St. Louis and other finance web site.

Multiple Linear Regression, Back Propagation Algorithm, and Support Vector Regression techniques were utilized to predict US unemployment rate. Based on Mean Squared Error and adjusted R2 values, the Support Vector Regression technique provided superior results for the given dataset. Future US unemployment rate was predicted with an average absolute error value of 0.815, 0.13 and 0.07 using MLR, ANN and SVR, respectively.

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Chapter 1: Introduction

1.1 Literature Review

Time series analysis and Okun's law are two basic approaches used to forecast unemployment rate. The time series data is an ordered sequence of values of a variable at equally spaced time intervals. The time series forecasting approach deals with developing models to predict future values based on time series data. The Okun's law approach is based on developing a statistical relationship between the unemployment rate and the rate of production losses. It is not based on time series data. Usually, there is a positive relationship between the Gross Domestic Product (GDP) and employment since the value of labor in the production defines the GDP. Okun's law states that GDP will decrease approximately 2% when unemployment increases for by 1% (Baily and Okun, 1965).

Time-Series Forecasting has three main tasks: 1) Develop a best possible model that relates available features to the unknown variable, 2) Use the model to predict the unknown variable, and 3) Obtain major properties of the model (Characterization). The three tasks may overlap with each other (Weigend and Gershenfeld, 1992).

The relationship between independent factors and unemployment rate can be linear or nonlinear. Many models presented in the literature assume a linear relationship. Proietti (2003) ~~has~~ explored performance of linear and nonlinear structural time series models of the US unemployment rate utilizing a test period of the last two decades. Studies, such as Altissimo and Violante (2001), Caner and Hansen (2001), Milas and Rothman (2008) utilized nonlinear models. Appropriate model selection and dependency of data are major problem in using nonlinear models. Olmedo (2014) used two different nonlinear models called reconstruction approach and Artificial Neural Networks (ANN) to predict Spanish unemployment rate and concluded that ANN outperformed the reconstruction approach in predicting Spanish unemployment rate.

Rothman (1998) analyzed the performance of six different nonlinear time series models versus linear model predictions and concluded that the nonlinear models perform much better based on Mean Squared Prediction Error (MSPE). Montgomery et al. (1998) compared the performance of different linear and nonlinear forecasting techniques using U.S. quarterly unemployment rate. Voineagu et al. (2012) developed a method to forecast the monthly unemployment rate which also highlights the seasonality of the data.

1.2 Problem Statement

The purpose of this study is to apply three different techniques to predict U.S. unemployment rate based on the historical data published by U.S. government. The three methods are: 1) Multiple Linear Regression (MLR), 2) Artificial Neural Networks (ANN), and 3) Support Vector Regression (SVR). The results of all three methods will be compared using R-Squared and MSE values to determine which technique is better suited to predict U.S. unemployment rate.

The main contribution of this study was identification of five economic factors: 1) Consumer Price Index (CPI), 2) Returned on Treasury Securities (RTS), 3) Total Nonfarm Payroll (TNP), 4) Jobless Claims Filed (JCF), and 5) Standard and Poor's 500 (SP500). The study applied three different methods on the same data set to predict US unemployment rate. Thus far, neither time series nor Okun's law have used the above five economic factors to forecast US unemployment rate.

Chapter 2: Prediction Methods

2.1 Multiple Linear Regressions (MLR)

Multiple linear regression is a multivariate statistical technique to study the linear correlations of a dependent variable (Y) with two or more independent variables (Xs). Table 1 shows all the notations for this method.

Table 1 - MLR Notations

Notation	Description
Y	Dependent Variable in the Regression Model
i	Independent Variable Index
X_i	Independent Variable i in the Regression Model
β_0	Intercept of the regression model
β_i	Coefficient of Variable i in the Regression Model
ε	Random Error Term

The general form of the model is shown in Equation 1.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \qquad (1)$$

ε represents the error term of the model and usually follows the normal distribution. β_0 is the intercept and $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients related to factors $X_1, X_2, \dots, X_n$ in the model, respectively. The independent variable (X_i) represent the value of variable i. Generalized least squares method is used to determine the coefficients of the model (Kissock et al., 2003). In this study, the U.S. unemployment rate is the dependent variable.

2.2 Artificial Neural Networks (ANN)

ANNs are computational models developed by Mcculloch et al. (1943). These models are based on neural networks in human brains. It consists of neurons and connections which are assigned a specific weight. The idea is to find appropriate weights for connections such an acceptable output can be gained for each corresponding input (Duda, et al., 2012). A neural network model also consists of layers. Each layer contains number of nodes. The first and last layers are called input and output layer respectively. Hidden layers are between input and output layers. Each node in a layer has inputs and generates an output based on an activation function (Duda, et al., 2012). The notations need for this method are listed in Table 2.

Table 2 - ANN Notations

Notation	Description
i	Indexes unit in input layer or the feature number
h	Indexes unit in hidden layer
Net_h	Scalar net activation of neuron k in hidden layer
H	Number of neurons in hidden layer
Net_o	Scalar net activation of output layer
OU_i	Output of neuron i in input layer
OU_h	Output of neuron k in hidden layer
δ	Sensitivity of neuron at output layer
δ_k	Sensitivity of neuron k at hidden layer
L	Learning rate
M	Number of data points
u	u-th pattern
x	Space of input patterns
y	Output vector
T	Target Vector
E	Error function in ANNs
Tre	Accepted error for BP
r	r-th epoch in back propagation algorithm
W_{ik}	Weight for connection from neuron i to neuron k in hidden layer
W_k	Weight for connection from neuron k in hidden layer to output layer

Different activation functions are shown in Equations 2, 3 and 4. Figure 1 shows the overall structure of the model.

$$\text{Sigmoid:}f(x) = \frac{1}{1+e^{-x}} \qquad 0< f(x) < 1 \tag{2}$$

$$\text{Tangent:}f(x) = \frac{e^{-x}-e^{-x}}{e^{-x}+e^{-x}} \qquad 0< f(x) < 1 \tag{3}$$

$$\text{Linear: } f(x) = x \tag{4}$$

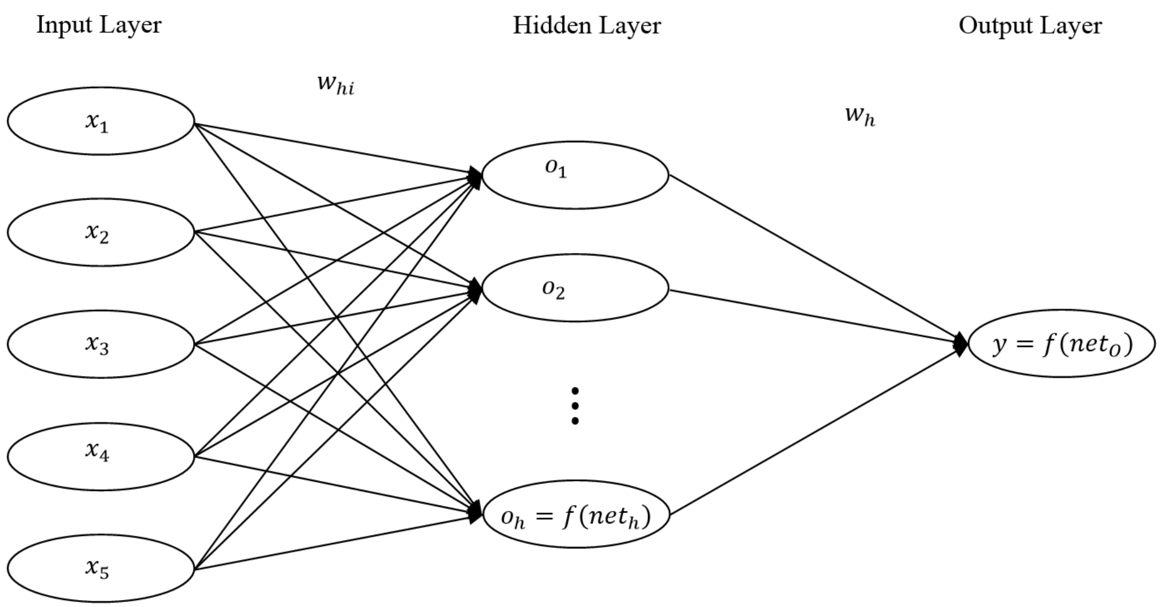

Figure 1–Artificial Neural Networks Structure

Input layer consists of five features demonstrating five factors. w_{hi} represents the weight for the connection between neuron i in input layer and neuron h in hidden layer and w_h shows the weights of the connections between neuron h in hidden layer and the single neuron in the output layer. net_h and net_O are the scalar net activation of neuron h in hidden layer and the neuron in the output layer, respectively.

2.2.1 Back Propagation Algorithm

After the weights are initialized, neural network utilizes Back Propagation Algorithm (BPA) to train the network. The back propagation algorithm was developed by Rumelhart (1988) and it is the most popular technique to train neural networks. The algorithm starts with an untrained network and explores better weight through using gradient descent algorithm. The BPA algorithm utilizes the error back propagated from the output layer to change weights. On each epoch of the algorithm outputs of the nodes are obtained based on weight of connections between nodes. The BPA can be summarized as following steps.

Feed Forward

Feed Forward is the first step in which the output of each neuron in hidden layer (OU_h) will be obtained using Equation 6. Equations 5 and 7 calculate scalar net activation of neuron h in hidden layer (net_h) and the scalar net activation of the single neuron in the output layer(net_O), respectively.

$$net_h = \sum_{i=0}^{5} x_i w_{hi} \tag{5}$$

$$OU_h = f(net_h) \tag{6}$$

$$net_O = \sum_{h} OU_h w_h \tag{7}$$

Feed Backward

Finally, Equation 8 is used to calculate the result of the output layer:

$$y = f(net_O) \tag{8}$$

In this step, the network error is back propagated from output layer to input layer. The sensitivity (δ) is calculated for the output node based on Equation 9 where t is the target value and y is the forecast value:

$$\delta = y(1 - y)(y - t) \tag{9}$$

According to Duda et al. (2012), the sensitivity of neuron h in hidden layer can be calculated for each node in hidden layer as shown in Equation 10.

$$\delta_{\mathrm{h}} = \mathrm{OU_k}(1 - \mathrm{OU_k})\, \delta\, w_h \tag{10}$$

Cost function is calculated using Equation 11. According to Equations 7 and 8, the network output is a function of weight vectors. Thus, cost is the function of $\mathrm{w_h}$ and $\mathrm{w_{hi}}$ where $h = 1, \ldots, H$ and $i = 1, \ldots, 5$.

$$\mathrm{E} = \frac{1}{2}(y - t)^2 \tag{11}$$

According to Duda et al. (2012), the BPA can be represented as follows where L is learning rate, r is the epoch number and Tre is the acceptable error or threshold value:

Back Propagation Algorithm

1. Initialize $w, L\ and\ r = 0$
2. Do $r \leftarrow r + 1$ (Update epoch)
3. $u \leftarrow 0; \Delta w_{hi} \leftarrow 0; \Delta w_h \leftarrow 0$
4. Do $u \leftarrow u + 1$
5. $x_u \leftarrow select\ pattern$
6. $\Delta w_{hi} \leftarrow \Delta w_{hi} + L.\delta_{\mathrm{h}}.x_i;\ \Delta w_h \leftarrow \Delta w_h + L.\delta.y$
7. Until $u = M$
8. $w_{hi} \leftarrow w_{hi} + \Delta w_{hi}; w_h \leftarrow w_h + \Delta w_h$
9. Until $\left||\nabla E(w)|\right| < Tre, \nabla E(w) = E_{r+1}(w) - E_r(w)$
10. Return w
11. End

2.3 Support Vector Regression (SVR)

Table 3 shows the notations for variables and parameters needed in this method.

Table 3 - SVR Notations

Notation	Description
x	Input vector
t	Target vector
u	Unit index of u-th pattern
v	Unit index of v-th pattern
y	Output vector
N	Number of data points
ϵ	The width of the tube (Acceptable Deviation)
w_{SVR}	Regression line weight vector in SVR
b	Bias term
ζ_u^+	Positive deviation from acceptable region for u-th pattern
ζ_u^-	Negative deviation from acceptable region for u-th pattern
C	Cost of not falling inside the SVR tube
L_ϵ	Loss function for the tube with width of ϵ
φ	The kernel function
σ	The sigma value of kernel function

Suppose a training data set is given as $\{(x_1, t_1), \dots, (x_u, t_u), \dots, (x_N, t_N)\}$ where $x_u \in R^m$ is the input vector and $t_u \in R$ is the target vector. The main goal is to obtain a flat function f(x) that has a deviation less than the maximum acceptable deviation (ε) from the actual targets t_u for every pattern of the training data. In other words, the error of each pattern less than ε is acceptable and deviation of more than ε is not acceptable.

Equation 12 defines $f(x_u)$ where w_{SVR} is the regression line weight vector of x_u in SVR and b is the bias term. To have simpler function, smaller sizes of w_{SVR} are recommended. Figure 2 represents the deviation range and the data patterns where ϵ is the width of the acceptable tube. (Vapnik, 2000)

$$f(x_u) = w_{SVR}^T x + b \tag{12}$$

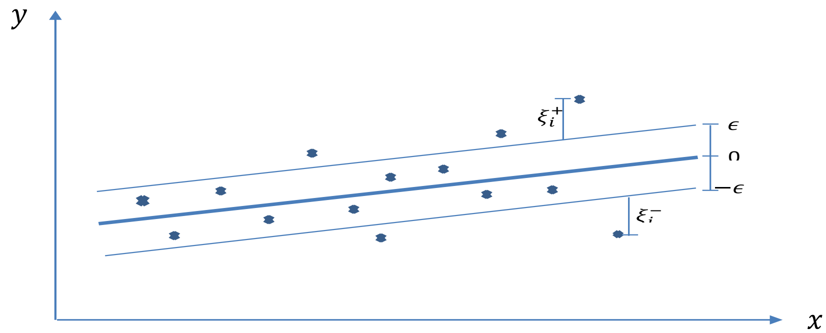

Figure 2 - Deviation in SVR

Equation 13 defines a loss function L_ϵ for a deviation size of ϵ which assigns a cost C for point outside of the predefined range (Vapnik, 2000).

$$L_\epsilon(x, t, f(x)) = \begin{cases} 0 & if\ |w_{SVR}^T x + b - t| \le \epsilon \\ |w_{SVR}^T x + b - t| - \epsilon & otherwise \end{cases} \quad \forall u \tag{13}$$

Equation 14 describes SVR minimization function subject to the constraints shown in Equations 15, 16 and 17. The term $\frac{1}{2} w_{SVR}^T w_{SVR}$ in the objective function is to minimize the size of the weights w_{SVR}. ζ_u^+ and ζ_u^- are positive and negative deviation from acceptable region for the u^{th} pattern, respectively. C is the cost of falling outside of the acceptable tube. Thus, the term $c \sum_{i=1}^{N} (\zeta_u^+ + \zeta_u^-)$ is the trade-off between minimizing the size of the weights and the loss function. A proper value of C is very important to avoid under-fitting or over-fitting problems (Vapnik, 2000).

$$minimize\ \frac{1}{2} w_{SVR}^T w_{SVR} + c \sum_{i=1}^{N} (\zeta_u^+ + \zeta_u^-) \tag{14}$$

Subject to:

$$w_{SVR}^T x + b - t_u < \epsilon + \zeta_u^+ \qquad \forall_u \tag{15}$$

$$t_u - \mathrm{w}_{\mathrm{SVR}}^{\mathrm{T}}\mathrm{x} - \mathrm{b} < \epsilon + \zeta_u^- \qquad \forall_u \qquad (16)$$

$$\zeta_u^+, \zeta_u^- \geq 0 \qquad \forall_u \qquad (17)$$

SVR exploits a kernel function (φ) to map $\mathrm{x_u} \in \mathrm{R^n}$ to higher dimensional feature space where theoretically exists a linear function f to formulate $f(x)$ as a function of input data x (Duda et al., 2012).

The regression function can be written as shown in Equation 18:

$$f(x) = w_{SVR}\varphi(x) + b \qquad \forall_u \qquad (18)$$

The kernel function can be defined using Equation 19:

$$\varphi(x_u, x_v) = \exp\left(-\frac{1}{2\sigma^2}\left|\left|x_u - x_v\right|\right|^2\right) \qquad \forall_u \qquad (19)$$

σ represents the standard deviation of the kernel function and is user identified. x_u and x_v are the u^{th} and v^{th} pattern in the input vector. In this study, complete enumeration (grid SVR) was applied to obtain the value of σ.

Chapter 3: Methodology

3.1 Economic Factor Selection

There are lots of economic indicators that can impact unemployment rate in the United States. In this study, five factors were selected for which monthly data is available from January 1993 to June 2014. The five factors are described below.

3.1.1 Consumer Price Index (CPI)

The Consumer Price Index (CPI) is defined by the Bureau of the Economic Analysis as a measure of the average monthly change in the price of goods and services paid by urban consumers between any two time periods (Bureau of Economic Analysis, 2013). To calculate the index, price changes are averaged with weights showing their importance in the spending of the particular group. The index measures price changes as a percent change from a predetermined reference date (Bureau of Economic Analysis, 2013). Variations in this index are used to evaluate price changes related to the cost of living. The data on CPI was downloaded from: http://research.stlouisfed.org/fred2/series/CPIAUCSL/.

3.1.2 Return on Treasury Securities (RTS)

Federal Reserve Board utilized Constant Maturity (CM) as a correction for equivalent maturity to find an index using the average yield of different Treasury securities maturing at various periods. These rates are released by the U.S. Treasury on a daily basis. In order to get the monthly data, the average method is used. The data on CM was downloaded from: http://research.stlouisfed.org/fred2/series/DGS10/.

3.1.3 Total Nonfarm Payroll (TNP)

The U.S. Bureau of Labor Statistics defines Total Nonfarm Payroll (TNP) as a measure of the number of U.S. workers in the economy which does not include proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed (Bureau of Labor statistics, 2013).

TNP represents number of jobs added to or lost in an economy. It can be concluded that the business is growing if employment number increase. This index is seasonally adjusted as the unemployment rate is subject to changes during the year because of different weather conditions, the time schools open and special holidays. The data on TNP was downloaded from: http://research.stlouisfed.org/fred2/series/PAYEMS/.

3.1.4 Jobless Claims Filed (JCF)

This index is the number of Jobless Claims Filed (JCF) by those who are willing to receive state jobless benefits. Financial analysts watch this value closely since it gives a good insight about the economy. The higher the initial claims, the weaker the economy. The data on JCF was downloaded from: http://research.stlouisfed.org/fred2/series/IC4WSA/.

3.1.5 Standard & Poor's 500 (SP500)

Standard and Poor's 500 (SP500) is a stock market index that keeps track of the 500 most commonly held stocks on the New York Stock Exchange (NYSE). These 500 stocks can give investors an overview of stock market. The standard and poor's 500 is also considered as an economic indicator and it project the performance of US economy. The data on S&P 500 was downloaded from: http://finance.yahoo.com.

3.2 Data collection

Most of the data are coming from the Federal Reserve Bank of St. Louis. The U.S. unemployment rates as the output of all three methods are also taken from Federal Reserve Bank.

Table 4 shows the matrix of input data to predict two periods ahead unemployment rate.

Table 4 - Data Collected to train and validate

DATE	CPI	RTS	TNP	JCF	S&P 500
Jan-93	142.80	6.60	109805	341200	438.78
Feb-93	143.10	6.26	110047	334813	443.38
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
Jun-14	237.69	2.60	138764	314375	1960.23

Table 5 shows all the descriptive statistics of five factors on all 258 data points. However, the descriptive statistics for training and test data set need to be calculated separately.

Table 5 - Descriptive Statistics on Data for five Factors

	CPI	RTS	TNP	JCF	SP500
Min	142.80	1.53	109805	269000	438.78
Max	237.69	7.96	138764	654875	1960.23
Mean	188.45	4.62	129118.99	366856.41	1101.60
Std	28.41	1.50	7509.95	67100.98	351.30
Range	94.89	6.43	28959	385875	1521.45

Figures 3 to 8 show the data on each factor from January 1993 to June 2014 in the United States including the unemployment rate.

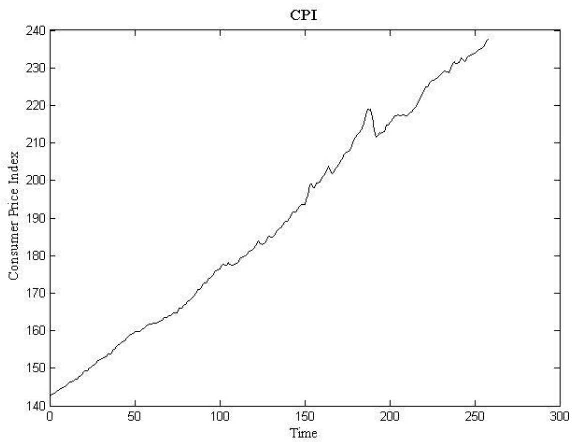

Figure 3 - Consumer Price Index

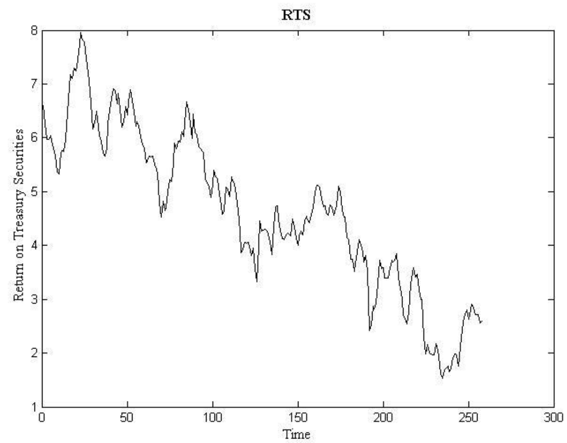

Figure 4 – Return on Treasury Securities

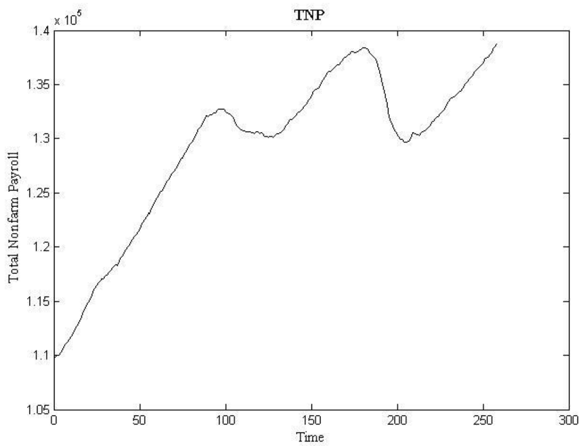

Figure 5 - Total Nonfarm Payroll

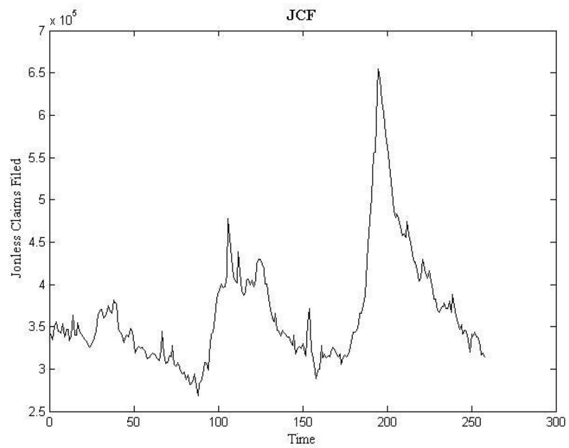

Figure 6 - Jobless Claims Filed

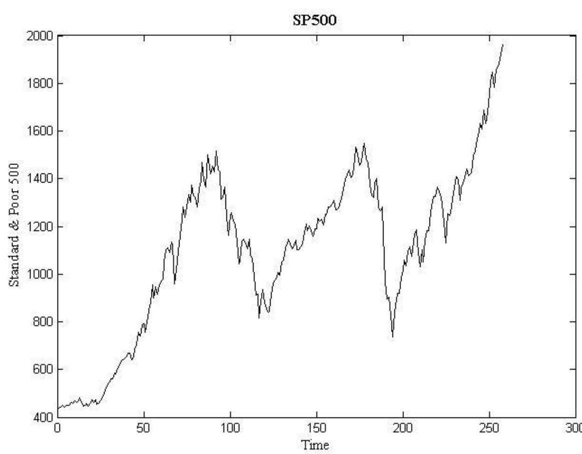

Figure 7 - Standard and Poor 500

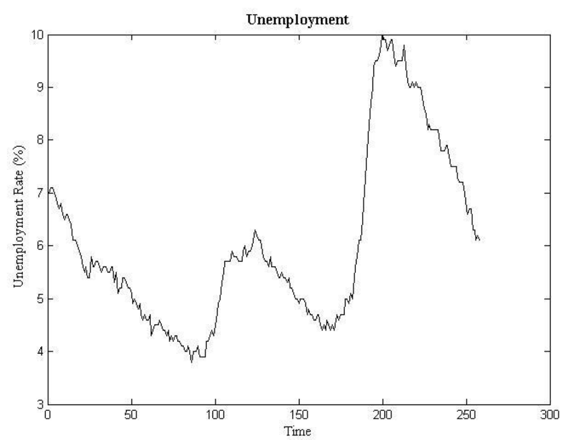

Figure 8 - US Unemployment Rate

3.3 Data Analysis

Each of the five variables has a different scale. To have the same scale for all features, data should be normalized according to Equation 20 using the minimum and maximum value of that feature. Equation 21 was used to un-normalize the data after the analysis is done. These equations force all Scaled X (SX) to in a range between -1 and +1.

$$SX = 2 * \frac{X - \min(X)}{\max(X) - \min(X)} - 1; \quad -1 \leq X_N \leq +1 \tag{20}$$

$$X = \frac{(SX + 1)(\max(X) - \min(X))}{2} + \min(X) \tag{21}$$

Chapter 4: Results and Analysis

The available data set was divided into two different sets: 1) Training set which is used to build the model; 2) Test data set which is not included in the training set and is used to validate the model. MLR, ANN and SVR were applied to the training data set using MATLAB 2014a. The percentages of dividing the data set into training and test are 80 and 20 which will be 207 and 51 data points, respectively. The approach to select 51 data points as test data set is to select every 5th point starting from the first data point. The remaining 207 values are under training data set. All the models are built and tested based on the normalized data. The results are described in details in the following sections. To check if all the variables are significant or not, stepwise regression is used before implementing those three techniques.

4.1 MLR Result

Stepwise regression was applied to the training data set to test how significant each variable was in the model. The purpose of this section is trying to find the confidents in Equation 22.

$$Y_t = \beta_0 + \beta_1 CPI_{t-2} + \beta_2 RTS_{t-2} + \beta_3 TNP_{t-2} + \beta_4 JCF_{t-2} + \beta_5 SP500_{t-2} + \varepsilon_t \quad (22)$$

The indexes of t and $t-2$ all refer to the time of the forecasting. This method can be applied in MATLAB environment and starts with no variable in the model. The variable with the highest correlation enters the model and is tested to see if it should be in the model or it can be taken out due to being insignificant. The results are shown in the following steps and the coefficients of the models in each step are summarized in Tables 6 to 10.

Step 1: JCF enters - R^2 = 0.584

Table 6 - Linear Regression Parameters when JCF is in model

Variable	Coefficient	Std. Error	t	P-value	95% Confidence Interval	
JCF	1.179	0.069	16.980	5.88E-41	1.043	1.316
Constant	0.308	0.042	7.379	3.88E-12	0.226	0.391

Both p-values in the table are smaller than 0.05. Therefore, it is concluded that both the constant and JCF should stay in the model.

Step 2: RTS enters - R^2 = 0.683

Table 7 - Linear Regression Parameter when RTS moves into the model

Variable	Coefficient	Std. Error	t	P-value	95% Confidence Interval	
RTS	-0.400	0.050	8.009	8.69E-14	-0.499	-0.302
JCF	0.944	0.067	14.005	1.13E-31	0.812	1.077
Constant	0.178	0.040	4.448	1.42E-05	0.099	0.257

All variables are significant in the model since all p-values are smaller than 0.05.

Step 3: TNP enters - R^2 = 0.835

Table 8 - Linear Regression Parameter when TNP moves into the model

Variable	Coefficient	Std. Error	t	P-value	95% Confidence Interval	
RTS	-0.909	0.052	-17.463	2.66E-42	-1.011	-0.806
TNP	-0.578	0.042	-13.612	2.07E-30	-0.662	-0.495
JCF	0.730	0.051	14.221	2.66E-32	0.629	0.832
Constant	0.240	0.029	8.174	3.18E-14	0.182	0.298

As p-values are smaller than the significance level 0.05, the model keeps all three variables.

Step 4: CPI enters - R^2 = 0.958

Table 9 - Linear Regression Parameter when CPI moves into the model

Variable	Coefficient	Std. Error	t	P-value	95% Confidence Interval	
CPI	0.951	0.038	24.576	1.28E-62	0.875	1.028
RTS	-0.142	0.041	-3.494	5.85E-4	-0.222	-0.062
TNP	-0.995	0.027	-36.526	6.16E-91	-1.048	-0.941
JCF	0.661	0.026	25.481	5.13E-65	0.609	0.711
Constant	0.407	0.016	25.070	6.21E-64	0.375	0.438

All the small p-values ae showing that no variable should be taken out from the model.

Step 5: SP500 moves in - R^2 = 0.961

Table 10 - Linear Regression Parameters when SP500 moves into the model

Variable	Coefficient	Std. Error	t	P-value	95% Confidence Interval	
CPI	0.917	0.041	22.387	1.68E-56	0.836	0.997
RTS	-0.125	0.041	-3.025	2.80E-03	-0.206	-0.043
TNP	-1.077	0.039	-27.480	5.35E-70	-1.154	-1.000
JCF	0.730	0.035	20.836	4.11E-52	0.661	0.800
SP500	0.153	0.047	3.145	1.79E-03	0.058	0.248
Constant	0.487	0.048	15.767	5.49E-37	0.426	0.548

Based on the stepwise regression results shown above, all variables are significant in the model and cannot be taken out because of the small p-values. Table 10 can also be represented as the result of MLR.

Table 11 shows the analysis of variance for the fitted model.

Table 11 - Analysis of Variance for Regression Model

Source	DF	Sum of Squares	Mean Square	F-Value	P-value
Regression	5	55.840	11.168	898.994	3.50E-139
Error	201	2.497	0.012		
Total	206	58.337			

Since F value is 898.994 and is much greater than $F_{0.05}(5,201) = 2.26$, there is enough evidence to reject the null hypothesis shown in Equation 23. That means all variables are significant in the model.

$$\begin{cases} H_0: \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0 \\ H_1: \beta_i \neq 0 \qquad\qquad \forall i = 0, \ldots, 5 \end{cases} \tag{23}$$

To forecast the unemployment rate for the test data set using MLR, Equation 24 can be used.

$$\begin{aligned} Y_t = 0.487 + 0.917CPI_{t-2} - 0.125RTS_{t-2} - 1.077TNP_{t-2} + 0.730JCF_{t-2} \\ + 0.153SP500_{t-2} + \varepsilon_t \end{aligned} \tag{24}$$

Figures 9 and 10 show the actual values of unemployment versus their prediction for the training set and test set using MLR, respectively.

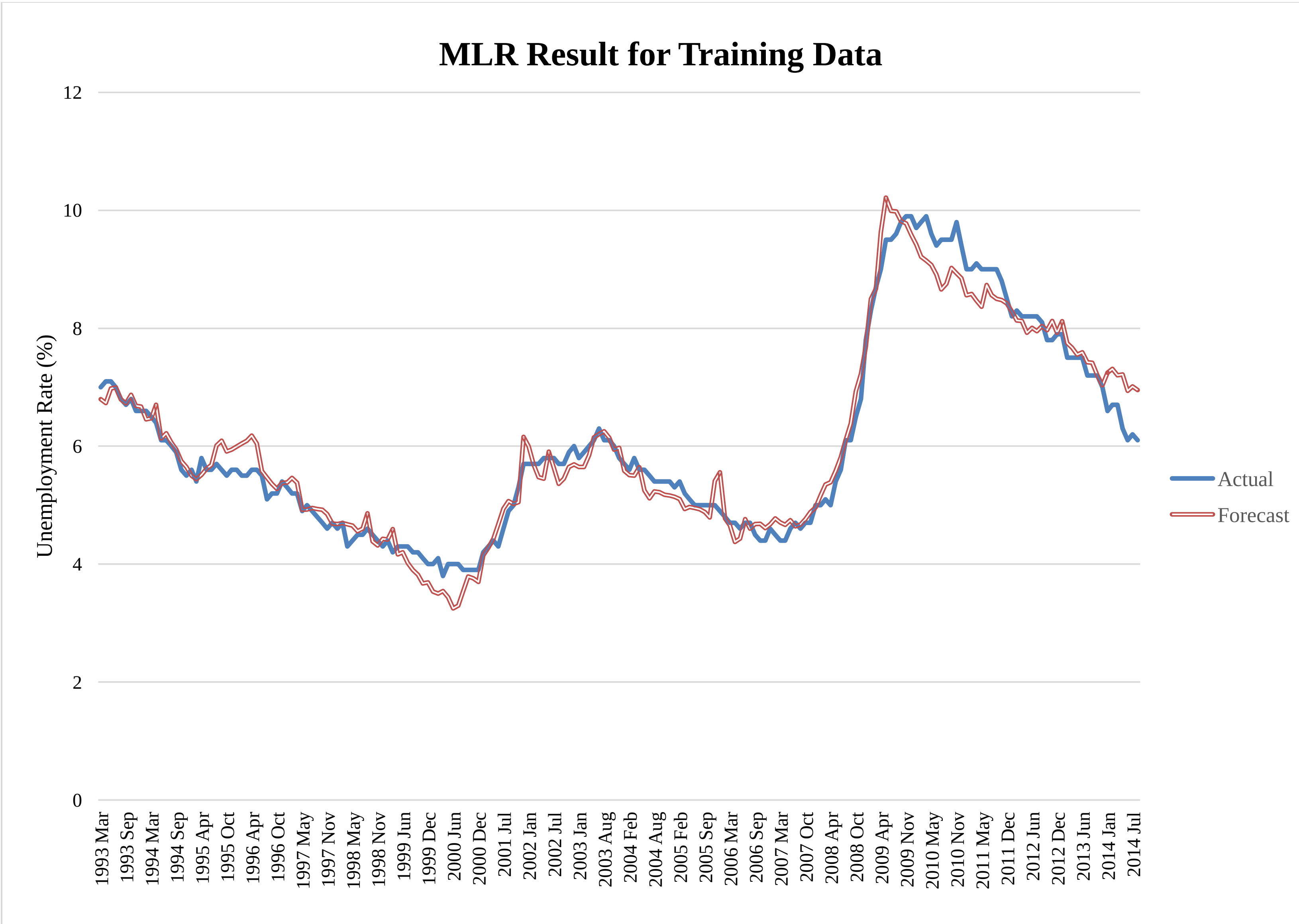

Figure 9 - MLR Training Result vs Actual Unemployment

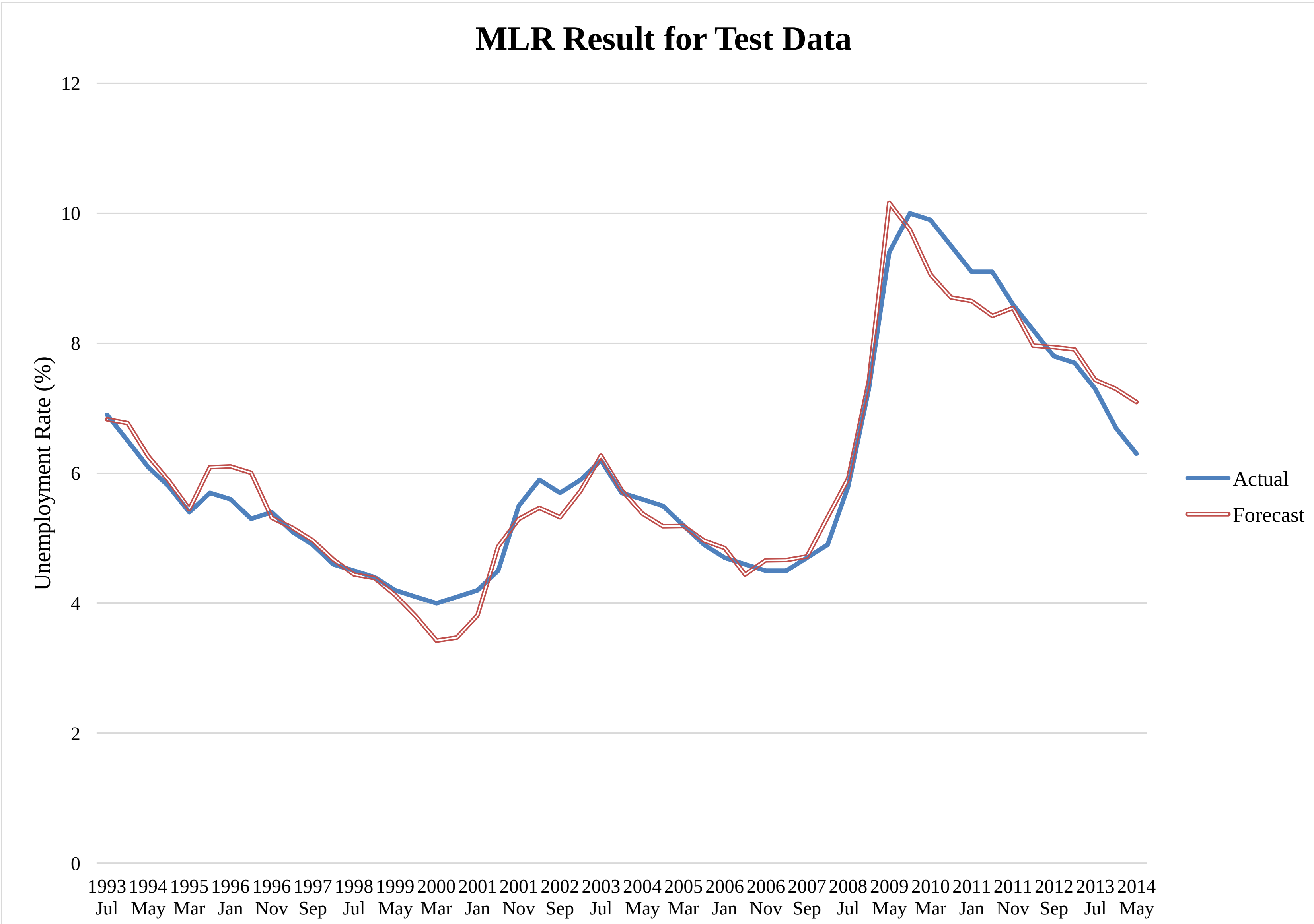

Figure 10 - MLR Test Result vs Actual Unemployment

4.1.1 Inference on MLR Results

What was obtained so far using MLR was a point estimate for unemployment rate for each month. Another way to infer regarding predicted values is the interval estimate. An interval estimate can be defined by a minimum value and a maximum value between which the parameter is said to lie with a probability of $(1-\alpha)100\%$.

Table 12 below shows the prediction interval for each one of the 51 data points in the test data set. It was investigated if the actual values are within the range of the prediction interval for each month in the test set (all 51 data points).

Table 12 - Prediction Interval on MLR Results

Min	Max	Actual Value	Forecast	In/Out
6.1	7.5	6.9	6.8	I
6.1	7.5	6.5	6.8	I
5.6	7.0	6.1	6.3	I
5.2	6.6	5.8	5.9	I
4.7	6.1	5.4	5.4	I
5.4	6.8	5.7	6.1	I
5.4	6.8	5.6	6.1	I
5.3	6.7	5.3	6.0	I
4.6	6.0	5.4	5.3	I
4.5	5.9	5.1	5.2	I
4.3	5.7	4.9	5.0	I
4.0	5.4	4.6	4.7	I
3.7	5.1	4.5	4.4	I
3.7	5.1	4.4	4.4	I
3.4	4.8	4.2	4.1	I
3.1	4.5	4.1	3.8	I
2.7	4.1	4	3.4	I
2.8	4.2	4.1	3.5	I
3.1	4.5	4.2	3.8	I
4.2	5.6	4.5	4.9	I
4.6	6.0	5.5	5.3	I
4.8	6.2	5.9	5.5	I
4.6	6.0	5.7	5.3	I
5.0	6.4	5.9	5.7	I
5.6	7.0	6.2	6.3	I
5.0	6.4	5.7	5.7	I

Prediction Interval on MLR Results (Cont'd)

Min	Max	Actual Value	Forecast	In/Out
4.7	6.1	5.6	5.4	I
4.5	5.9	5.5	5.2	I
4.5	5.9	5.2	5.2	I
4.3	5.7	4.9	5.0	I
4.1	5.5	4.7	4.8	I
3.7	5.1	4.6	4.4	I
4.0	5.4	4.5	4.7	I
4.0	5.4	4.5	4.7	I
4.0	5.4	4.7	4.7	I
4.6	6.0	4.9	5.3	I
5.2	6.6	5.8	5.9	I
6.7	8.1	7.3	7.4	I
9.5	10.9	9.4	10.2	O
9.1	10.5	10	9.8	I
8.4	9.8	9.9	9.1	O
8.0	9.4	9.5	8.7	O
8.0	9.4	9.1	8.7	I
7.7	9.1	9.1	8.4	I
7.8	9.2	8.6	8.5	I
7.3	8.7	8.2	8.0	I
7.2	8.6	7.8	7.9	I
7.2	8.6	7.7	7.9	I
6.7	8.1	7.3	7.4	I
6.6	8.0	6.7	7.3	I
6.4	7.8	6.3	7.1	O

Column 5 of Table 12 shows if the actual value of the unemployment rate falls Inside (I) or Outside (O) of the prediction interval. Out of 51 data points, 4 unemployment rate fall outside of the boundaries which show a 92.1% accuracy in the prediction model using MLR.

4.2 ANN Result

In this approach, same 207 data points as in MLR were considered to train the model. The remaining 51 data points were used to test the model. The sigmoid function was used in the training process.

The approach to test different learning rates was starting from 0.05 and increasing it by 0.05 every time. The model was run with the new learning rate and the results were analyzed. Learning rate of 0.05 gave the best results with the highest R-Squared value compared to other learning rates for this data set.

Also, one hidden layer and two-hidden layer models were tested with all possible number of neurons from 1 to 20. The 1-hidden layer with 18 neuron model gave the smallest variance among all those tested. Figures 11 and 12 show the ANN results versus actual unemployment rates for the training data set and test data set, respectively.

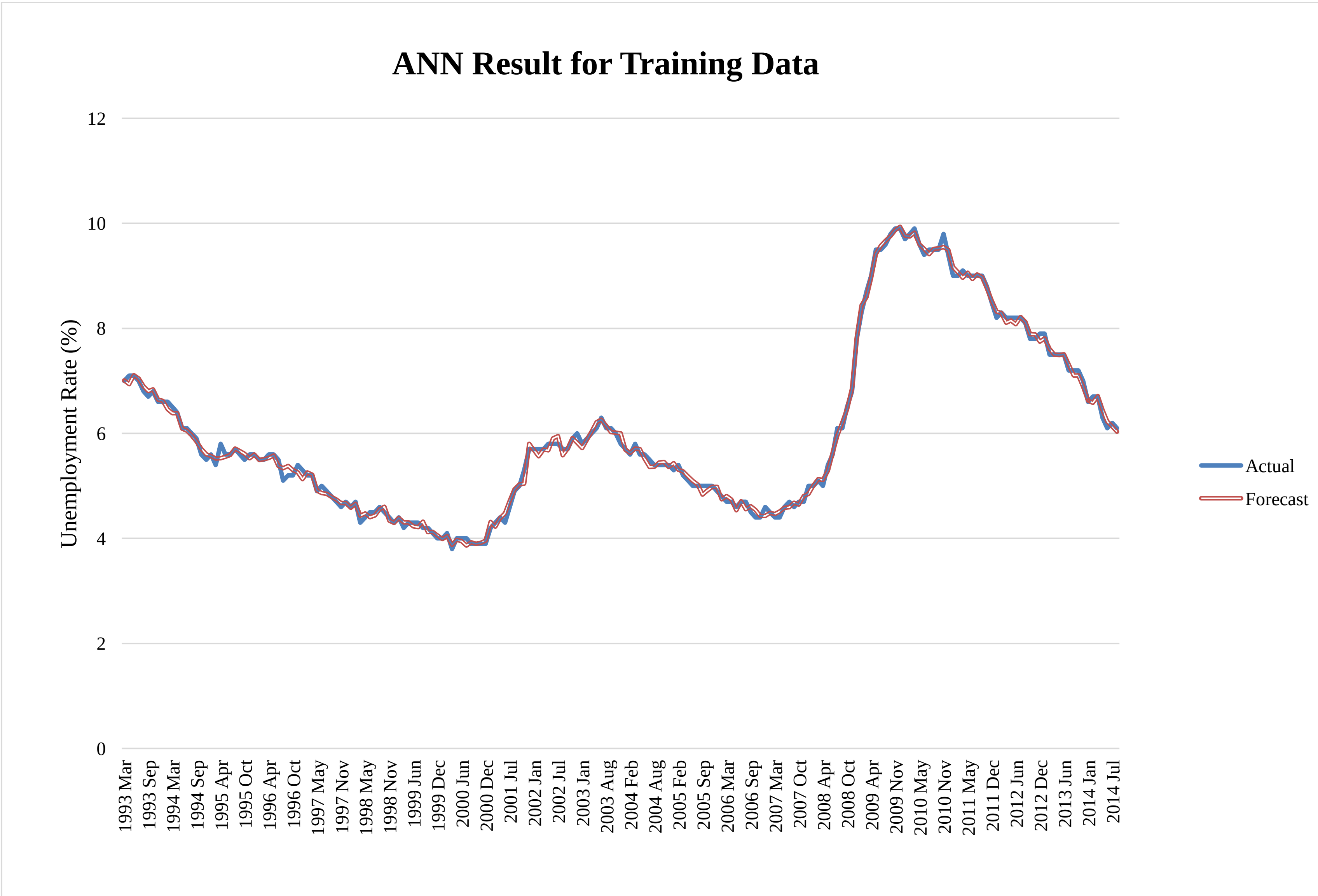

Figure 11 - ANN Training Result vs Actual Unemployment

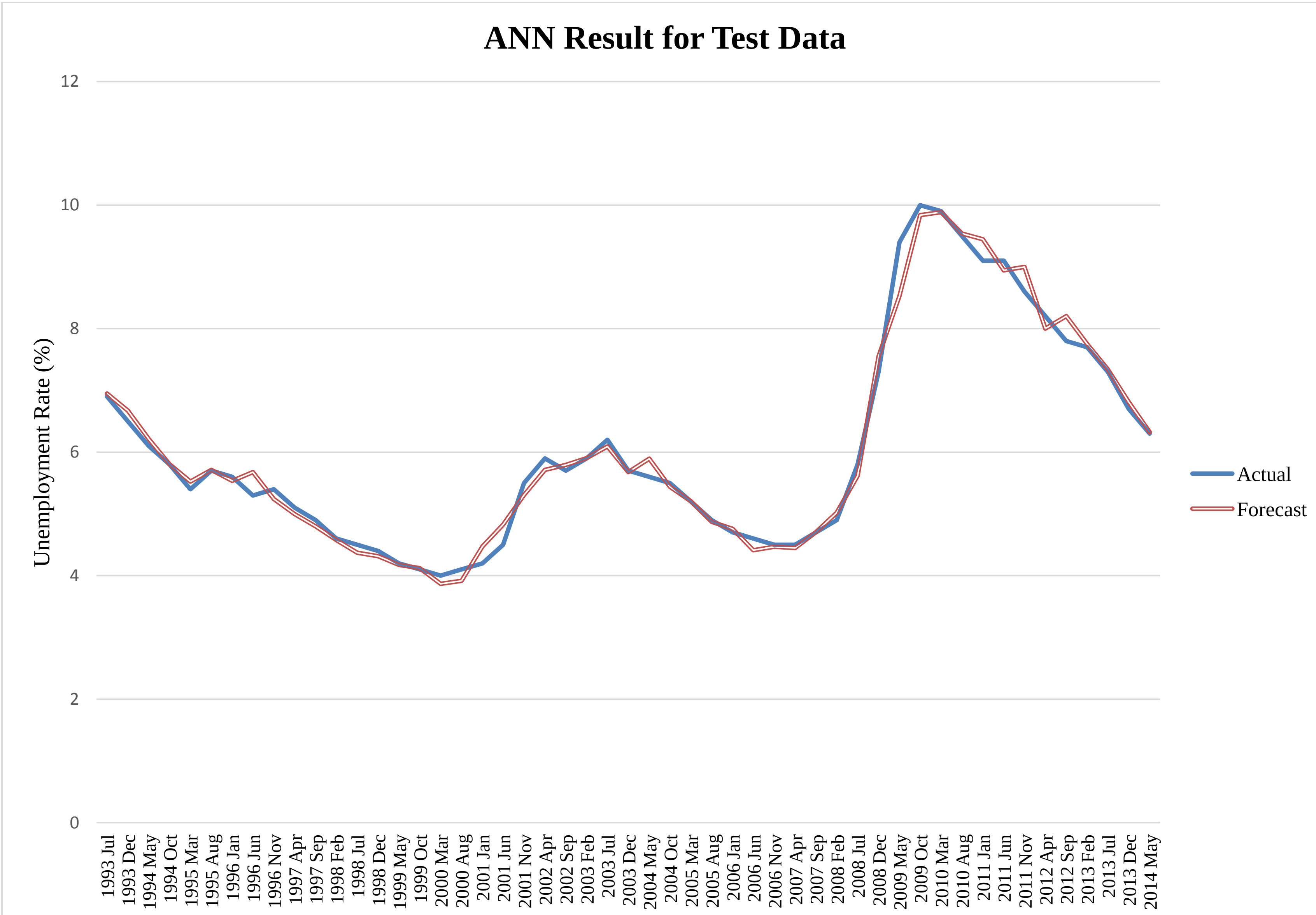

Figure 12 - ANN Test Result vs Actual Unemployment

4.2.1 Inference on ANN Result

The prediction intervals on ANN results show that 98% of the prediction intervals include the actual value of unemployment rate for the test data. The boundaries and comparisons are shown in Table 13.

Table 13 - Prediction Intervals on ANN Results

Min	Max	Actual Value	Forecast	In/Out
6.2	7.6	6.9	6.9	I
6	7.4	6.5	6.7	I
5.5	6.9	6.1	6.2	I
5.1	6.5	5.8	5.8	I
4.8	6.2	5.4	5.5	I
5	6.4	5.7	5.7	I
4.8	6.2	5.6	5.5	I
5	6.4	5.3	5.7	I
4.5	5.9	5.4	5.2	I
4.3	5.7	5.1	5.0	I
4.1	5.5	4.9	4.8	I
3.9	5.3	4.6	4.6	I
3.7	5.1	4.5	4.4	I
3.6	5	4.4	4.3	I
3.5	4.9	4.2	4.2	I
3.4	4.8	4.1	4.1	I
3.2	4.6	4	3.9	I
3.2	4.6	4.1	3.9	I
3.8	5.2	4.2	4.5	I
4.1	5.5	4.5	4.8	I
4.6	6	5.5	5.3	I
5	6.4	5.9	5.7	I
5.1	6.5	5.7	5.8	I
5.2	6.6	5.9	5.9	I
5.4	6.8	6.2	6.1	I
5	6.4	5.7	5.7	I
5.2	6.6	5.6	5.9	I
4.7	6.1	5.5	5.4	I
4.5	5.9	5.2	5.2	I
4.2	5.6	4.9	4.9	I
4.1	5.5	4.7	4.8	I
3.7	5.1	4.6	4.4	I

Prediction Interval on ANN Results (Cont'd)

Min	Max	Actual Value	Forecast	In/Out
3.8	5.2	4.5	4.5	I
3.7	5.1	4.5	4.4	I
4	5.4	4.7	4.7	I
4.3	5.7	4.9	5.0	I
4.9	6.3	5.8	5.6	I
6.9	8.3	7.3	7.6	I
7.8	9.2	9.4	8.5	O
9.1	10.5	10	9.8	I
9.2	10.6	9.9	9.9	I
8.8	10.2	9.5	9.5	I
8.7	10.1	9.1	9.4	I
8.2	9.6	9.1	8.9	I
8.3	9.7	8.6	9.0	I
7.3	8.7	8.2	8.0	I
7.5	8.9	7.8	8.2	I
7.1	8.5	7.7	7.8	I
6.6	8	7.3	7.3	I
6.1	7.5	6.7	6.8	I
5.6	7	6.3	6.3	I

4.3 SVR Result

The SVR method used the same training and test data sets. This method was run 100 times and the results of the best among them were selected. Getting the same results was the reason why additional runs were not carried out.

The type of the kernel function used in SVR method was Radial Basis Function (RBF). The parameters that gave the better model are shown in Table 14 below.

Table 14 - SVR Model Parameters

Parameter	value
ε	0.003
C	247
σ	0.15

The result of the training and test processes in comparison to the actual unemployment rate are shown in Figures 13 and 14, respectively.

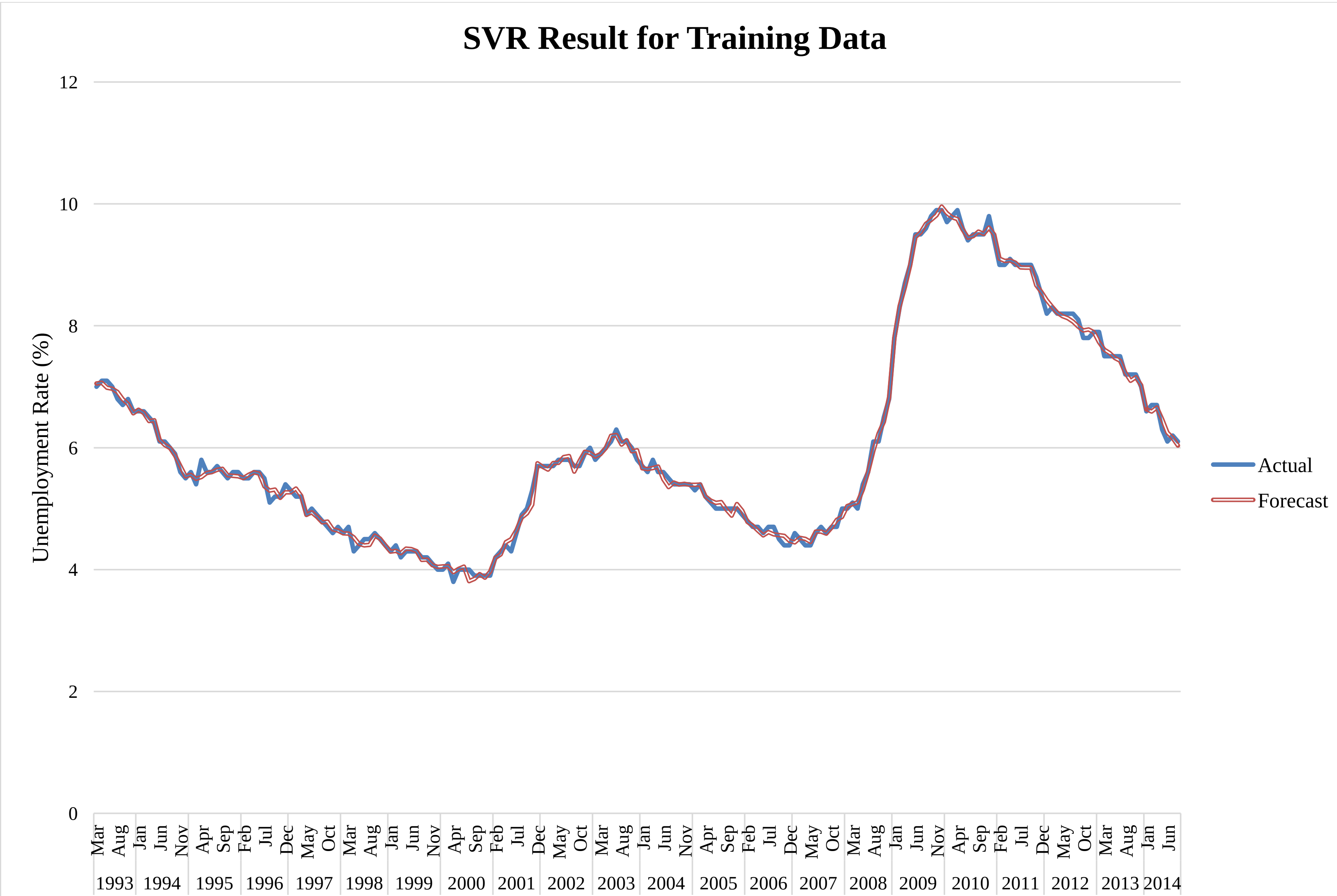

Figure 13 - SVR Training Result vs Actual Unemployment

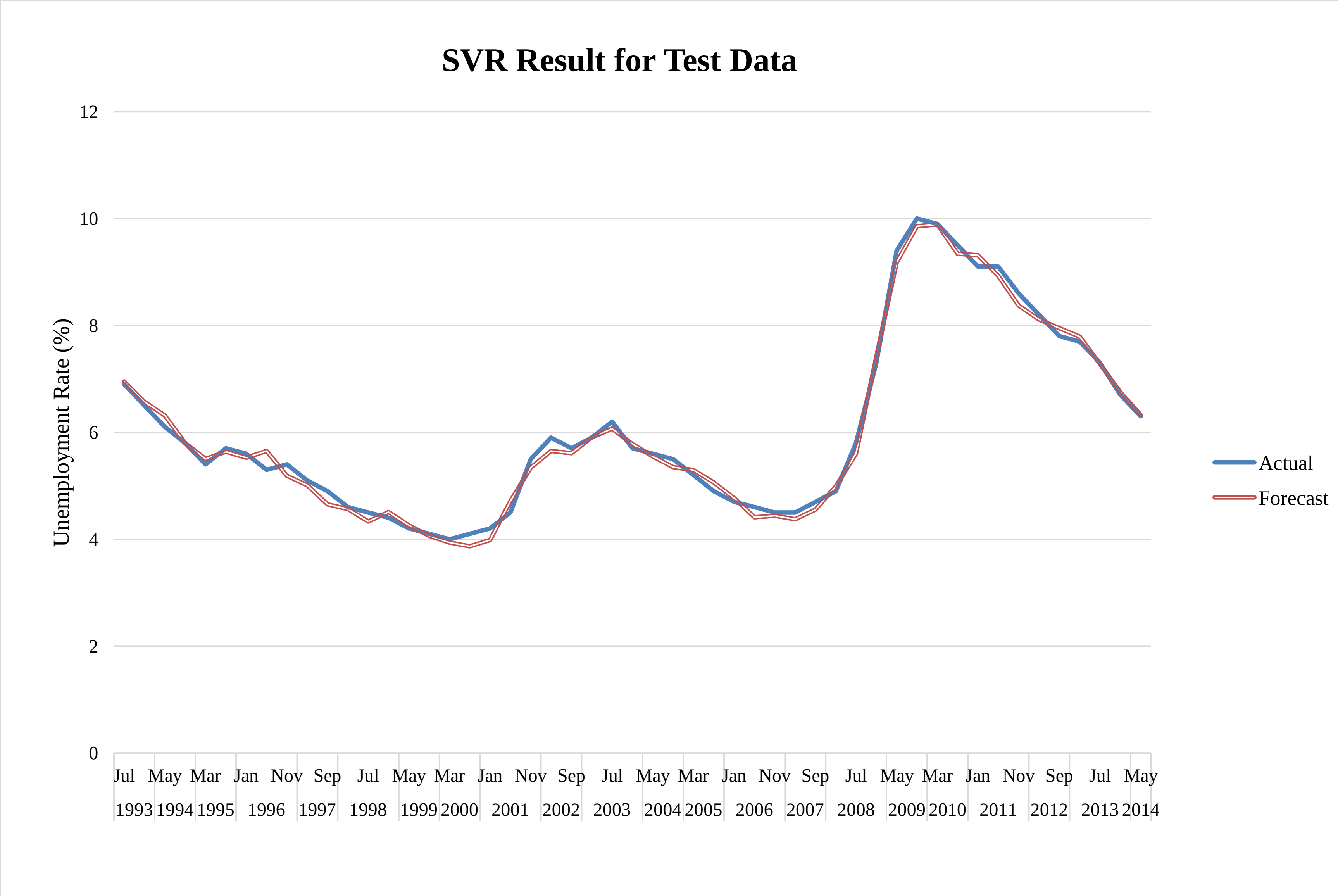

Figure 14 - SVR Test Result vs Actual Unemployment

4.3.1 Inference on SVR Results

Using SVR predicted results, the following prediction intervals were obtained that are shown in Table 15. These prediction intervals all include the actual values on unemployment rate which shows a 100% accuracy of SVR prediction model on this data set.

Table 15 - Prediction Interval on SVR Results

Min	Max	Actual Value	Forecast	In/Out
6.2	7.6	6.9	6.9	I
5.9	7.3	6.5	6.6	I
5.6	7	6.1	6.3	I
5.1	6.5	5.8	5.8	I
4.8	6.2	5.4	5.5	I
4.9	6.3	5.7	5.6	I
4.8	6.2	5.6	5.5	I
5	6.4	5.3	5.7	I
4.5	5.9	5.4	5.2	I
4.3	5.7	5.1	5.0	I
4	5.4	4.9	4.7	I
3.9	5.3	4.6	4.6	I
3.6	5	4.5	4.3	I
3.8	5.2	4.4	4.5	I
3.6	5	4.2	4.3	I
3.4	4.8	4.1	4.1	I
3.2	4.6	4	3.9	I
3.2	4.6	4.1	3.9	I
3.3	4.7	4.2	4.0	I
4	5.4	4.5	4.7	I
4.6	6	5.5	5.3	I
5	6.4	5.9	5.7	I
4.9	6.3	5.7	5.6	I
5.2	6.6	5.9	5.9	I
5.4	6.8	6.2	6.1	I
5.1	6.5	5.7	5.8	I
4.9	6.3	5.6	5.6	I
4.6	6	5.5	5.3	I
4.6	6	5.2	5.3	I
4.4	5.8	4.9	5.1	I
4.1	5.5	4.7	4.8	I
3.7	5.1	4.6	4.4	I

Prediction Interval on SVR Results (Cont'd)

Min	Max	Actual Value	Forecast	In/Out
3.7	5.1	4.5	4.4	I
3.7	5.1	4.5	4.4	I
3.9	5.3	4.7	4.6	I
4.3	5.7	4.9	5.0	I
4.9	6.3	5.8	5.6	I
6.7	8.1	7.3	7.4	I
8.5	9.9	9.4	9.2	I
9.2	10.6	10	9.9	I
9.2	10.6	9.9	9.9	I
8.6	10	9.5	9.3	I
8.6	10	9.1	9.3	I
8.2	9.6	9.1	8.9	I
7.7	9.1	8.6	8.4	I
7.4	8.8	8.2	8.1	I
7.2	8.6	7.8	7.9	I
7.1	8.5	7.7	7.8	I
6.6	8	7.3	7.3	I
6.1	7.5	6.7	6.8	I
5.6	7	6.3	6.3	I

Table 16 shows the prediction intervals for all three methods for easier comparison.

Table 16 - Prediction Intervals Summary

Year	Month	MLR PI	ANN PI	SVR PI	Actual
1993	Jul	(6.1 , 7.5)	(6.2 , 7.6)	(6.2 , 7.6)	6.9
1993	Dec	(6.1 , 7.5)	(6 , 7.4)	(5.9 , 7.3)	6.5
1994	May	(5.6 , 7)	(5.5 , 6.9)	(5.6 , 7)	6.1
1994	Oct	(5.2 , 6.6)	(5.1 , 6.5)	(5.1 , 6.5)	5.8
1995	Mar	(4.7 , 6.1)	(4.8 , 6.2)	(4.8 , 6.2)	5.4
1995	Aug	(5.4 , 6.8)	(5 , 6.4)	(4.9 , 6.3)	5.7
1996	Jan	(5.4 , 6.8)	(4.8 , 6.2)	(4.8 , 6.2)	5.6
1996	Jun	(5.3 , 6.7)	(5 , 6.4)	(5 , 6.4)	5.3
1996	Nov	(4.6 , 6)	(4.5 , 5.9)	(4.5 , 5.9)	5.4
1997	Apr	(4.5 , 5.9)	(4.3 , 5.7)	(4.3 , 5.7)	5.1
1997	Sep	(4.3 , 5.7)	(4.1 , 5.5)	(4 , 5.4)	4.9
1998	Feb	(4 , 5.4)	(3.9 , 5.3)	(3.9 , 5.3)	4.6
1998	Jul	(3.7 , 5.1)	(3.7 , 5.1)	(3.6 , 5)	4.5
1998	Dec	(3.7 , 5.1)	(3.6 , 5)	(3.8 , 5.2)	4.4

Prediction Intervals Summary (Cont'd)

Year	Month	MLR PI	ANN PI	SVR PI	Actual
1999	May	(3.4 , 4.8)	(3.5 , 4.9)	(3.6 , 5)	4.2
1999	Oct	(3.1 , 4.5)	(3.4 , 4.8)	(3.4 , 4.8)	4.1
2000	Mar	(2.7 , 4.1)	(3.2 , 4.6)	(3.2 , 4.6)	4
2000	Aug	(2.8 , 4.2)	(3.2 , 4.6)	(3.2 , 4.6)	4.1
2001	Jan	(3.1 , 4.5)	(3.8 , 5.2)	(3.3 , 4.7)	4.2
2001	Jun	(4.2 , 5.6)	(4.1 , 5.5)	(4 , 5.4)	4.5
2001	Nov	(4.6 , 6)	(4.6 , 6)	(4.6 , 6)	5.5
2002	Apr	(4.8 , 6.2)	(5 , 6.4)	(5 , 6.4)	5.9
2002	Sep	(4.6 , 6)	(5.1 , 6.5)	(4.9 , 6.3)	5.7
2003	Feb	(5 , 6.4)	(5.2 , 6.6)	(5.2 , 6.6)	5.9
2003	Jul	(5.6 , 7)	(5.4 , 6.8)	(5.4 , 6.8)	6.2
2003	Dec	(5 , 6.4)	(5 , 6.4)	(5.1 , 6.5)	5.7
2004	May	(4.7 , 6.1)	(5.2 , 6.6)	(4.9 , 6.3)	5.6
2004	Oct	(4.5 , 5.9)	(4.7 , 6.1)	(4.6 , 6)	5.5
2005	Mar	(4.5 , 5.9)	(4.5 , 5.9)	(4.6 , 6)	5.2
2005	Aug	(4.3 , 5.7)	(4.2 , 5.6)	(4.4 , 5.8)	4.9
2006	Jan	(4.1 , 5.5)	(4.1 , 5.5)	(4.1 , 5.5)	4.7
2006	Jun	(3.7 , 5.1)	(3.7 , 5.1)	(3.7 , 5.1)	4.6
2006	Nov	(4 , 5.4)	(3.8 , 5.2)	(3.7 , 5.1)	4.5
2007	Apr	(4 , 5.4)	(3.7 , 5.1)	(3.7 , 5.1)	4.5
2007	Sep	(4 , 5.4)	(4 , 5.4)	(3.9 , 5.3)	4.7
2008	Feb	(4.6 , 6)	(4.3 , 5.7)	(4.3 , 5.7)	4.9
2008	Jul	(5.2 , 6.6)	(4.9 , 6.3)	(4.9 , 6.3)	5.8
2008	Dec	(6.7 , 8.1)	(6.9 , 8.3)	(6.7 , 8.1)	7.3
2009	May	(9.5 , 10.9)	(7.8 , 9.2)	(8.5 , 9.9)	9.4
2009	Oct	(9.1 , 10.5)	(9.1 , 10.5)	(9.2 , 10.6)	10
2010	Mar	(8.4 , 9.8)	(9.2 , 10.6)	(9.2 , 10.6)	9.9
2010	Aug	(8 , 9.4)	(8.8 , 10.2)	(8.6 , 10)	9.5
2011	Jan	(8 , 9.4)	(8.7 , 10.1)	(8.6 , 10)	9.1
2011	Jun	(7.7 , 9.1)	(8.2 , 9.6)	(8.2 , 9.6)	9.1
2011	Nov	(7.8 , 9.2)	(8.3 , 9.7)	(7.7 , 9.1)	8.6
2012	Apr	(7.3 , 8.7)	(7.3 , 8.7)	(7.4 , 8.8)	8.2
2012	Sep	(7.2 , 8.6)	(7.5 , 8.9)	(7.2 , 8.6)	7.8
2013	Feb	(7.2 , 8.6)	(7.1 , 8.5)	(7.1 , 8.5)	7.7
2013	Jul	(6.7 , 8.1)	(6.6 , 8)	(6.6 , 8)	7.3
2013	Dec	(6.6 , 8)	(6.1 , 7.5)	(6.1 , 7.5)	6.7
2014	May	(6.4 , 7.8)	(5.6 , 7)	(5.6 , 7)	6.3
Accuracy %		92.1%	98%	100%	

4.4 R-Squared and MSE Values

The accuracy of the models was determined based on both the adjusted R-squared and Mean Squared Errors (MSE). Table 17 below shows the adjusted-R^2 and MSE values for test data set for all three techniques. It shows that SVR outperforms other two techniques on this data set with respect to both R-squared and MSE.

Table 17 - Comparative Results

Method	Adjusted R-squared	MSE
MLR	0.951	0.048
ANN	0.985	0.015
SVR	**0.992***	**0.007***

Chapter 5: Conclusion

It has always been crucial for governments to predict and try to decrease the unemployment rate. Several methods and techniques have been used to forecast unemployment rate in the literature. However, none of them used economic factors to forecast the unemployment rate. In this study, a model was developed such that the unemployment rate can be predicted using the value of those economic factors in the previous periods for the first time. Five different factors were used for each month to forecast the unemployment rate for two months ahead. The available data set was divided into two different sets to build and test the model. The validation process was done inside the training step. MLR, ANN and SVR techniques were used to predict the unemployment rates and the results were compared. It was shown that Support Vector Regression gave the better results on this data set. All the results for all techniques and the actual values are shown in Figure 15 for the test data set for easier comparison.

Also, prediction intervals for all 51 points were calculated to check how many of them included the actual unemployment rate. The results summarized in Table 16 showed that MLR includes 92.1% of the actual values, ANN includes 98% and SVR includes 100% of the actual values on this data set. Percentage of accuracy is a ratio of the number of prediction intervals that include the actual value over the total which is 51.

The results of future forecast for September and October 2014 is shown in Table 18 for all three methods.

Table 18 - Future Forecast based on the Trained Models

Date	MLR	ANN	SVR	Actual
Sep-14	6.71	6.12	5.96	5.90
Oct-14	6.62	5.76	5.88	5.80

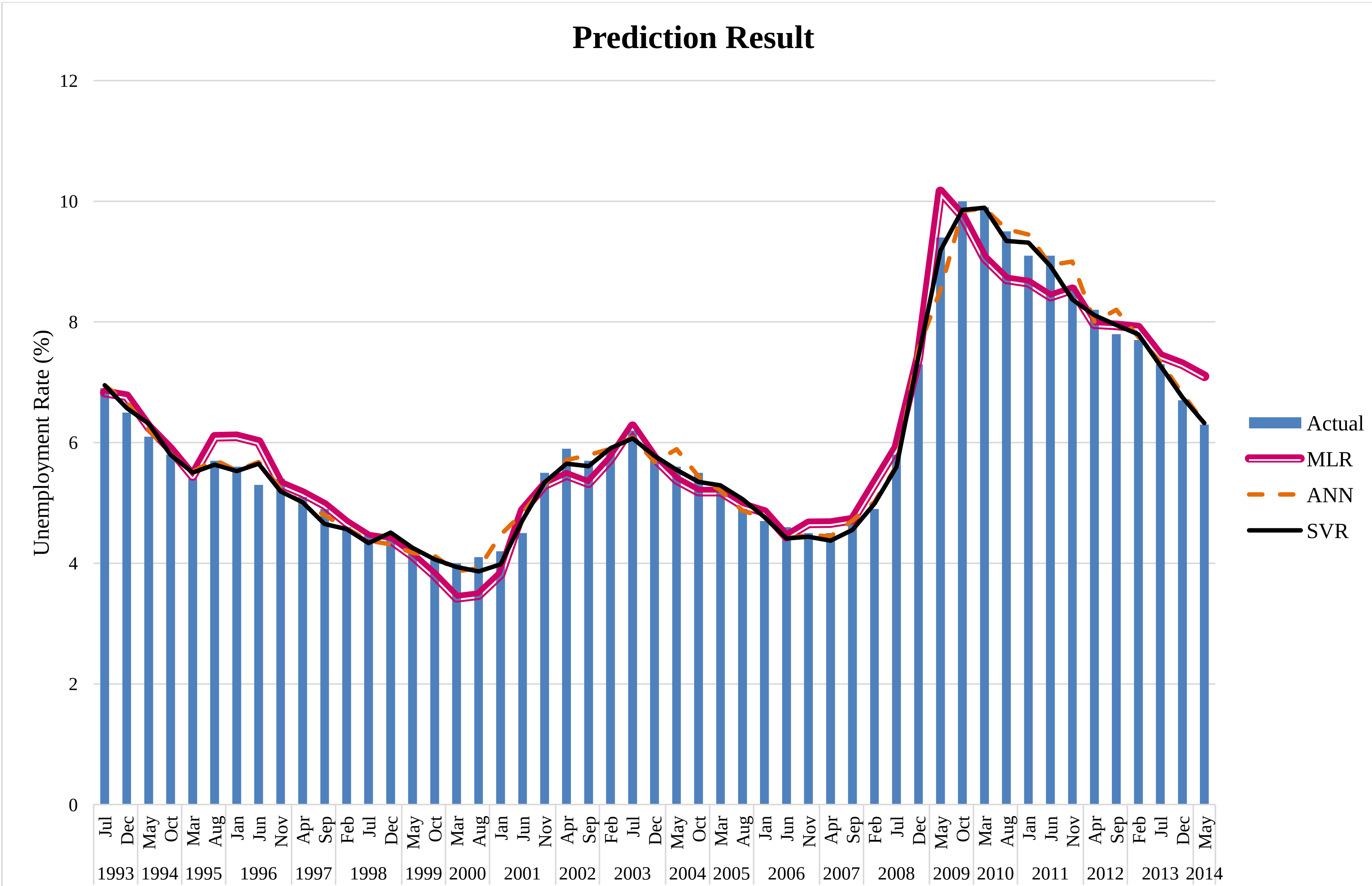

Figure 15 - Test Results for all Techniques vs. Actual Unemployment

5.1 Future Work

Unemployment rate considered as an important factor in countries economy and depends on different factors. This study explored five different economic factors to predict unemployment rate. Considering more factors for future work studies may improve the prediction quality. All the methods of this study were applying deterministic data where in reality data is more stochastic rather than deterministic. It could be a good contribution if fuzzy data were considered for unemployment estimation because of fluctuation in the nature of the data. There are a lot of different methods available including heuristic techniques that have great performance depending on the situation. Those methods can also be explored for future studies of unemployment rate.

Using quadratic terms for regression model may improve the results. Considering the value of unemployment rates for historical data can also be included as another factor to forecast future unemployment rate. There are several other regression techniques that can be tried on this data set to improve the results such as quantile regression.

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Appendix A: Input Data

To forecast the unemployment rate in February 1993, the values of those five variables in January 1993 are used.

Variable	***Definition***
CPI	Average monthly change in the price of goods/services paid by urban consumers between any two time periods
RTS	Correction for equivalent maturity to find an index using the average yield of different returned treasury securities maturing at various periods
TNP	Number of jobs added to an economy or lost in it
JCF	Number of jobless claims filed by those who are willing to receive state jobless benefits
SP500	An economic indicator that shows the whole U.S. stock market by keeping track of the 500 most commonly held stock on NYSE

Date	**CPI**	**RTS**	**TNP**	**JCF**	**SP500**
Jan-93	142.800	6.60	109805	341200	438.78
Feb-93	143.100	6.26	110047	334813	443.38
Mar-93	143.300	5.98	109998	350313	451.67
Apr-93	143.800	5.97	110306	355688	440.19
May-93	144.200	6.04	110573	345050	450.19
Jun-93	144.300	5.96	110754	344188	450.53
Jul-93	144.500	5.81	111053	341800	448.13
Aug-93	144.800	5.68	111212	353438	463.56
Sep-93	145.000	5.36	111451	337750	458.93
Oct-93	145.600	5.33	111737	346950	467.83
Nov-93	146.000	5.72	111999	346438	461.79
Dec-93	146.300	5.77	112311	332875	466.45
Jan-94	146.300	5.75	112583	338750	481.61
Feb-94	146.700	5.97	112783	363250	467.14
Mar-94	147.100	6.48	113248	340000	445.77
Apr-94	147.200	6.97	113597	340150	450.91
May-94	147.500	7.18	113931	354625	456.5
Jun-94	147.900	7.10	114247	345313	444.27
Jul-94	148.400	7.30	114624	341600	458.26
Aug-94	149.000	7.24	114902	337813	475.49
Sep-94	149.300	7.46	115253	334125	462.71
Oct-94	149.400	7.74	115468	331900	472.35

Date	CPI	RTS	TNP	JCF	SP500
Nov-94	149.800	7.96	115887	329250	453.69
Dec-94	150.100	7.81	116162	325850	459.27
Jan-95	150.500	7.78	116487	330125	470.42
Feb-95	150.900	7.47	116691	333188	487.39
Mar-95	151.200	7.20	116913	341063	500.71
Apr-95	151.800	7.06	117075	344250	514.71
May-95	152.100	6.63	117059	364375	533.4
Jun-95	152.400	6.17	117294	369063	544.75
Jul-95	152.600	6.28	117395	370150	562.06
Aug-95	152.900	6.49	117644	360500	561.88
Sep-95	153.100	6.20	117885	362350	584.41
Oct-95	153.500	6.04	118041	366188	581.5
Nov-95	153.700	5.93	118189	374938	605.37
Dec-95	153.900	5.71	118321	368350	615.93
Jan-96	154.700	5.65	118303	366125	636.02
Feb-96	155.000	5.81	118735	382000	640.43
Mar-96	155.500	6.27	119001	378050	645.5
Apr-96	156.100	6.51	119165	377563	654.17
May-96	156.400	6.74	119485	347688	669.12
Jun-96	156.700	6.91	119774	344000	670.63
Jul-96	157.000	6.87	120029	339688	639.95
Aug-96	157.200	6.64	120202	331550	651.99
Sep-96	157.700	6.83	120427	337188	687.33
Oct-96	158.200	6.53	120677	340625	705.27
Nov-96	158.700	6.20	120976	337800	757.02
Dec-96	159.100	6.30	121146	347813	740.74
Jan-97	159.400	6.58	121382	344563	786.16
Feb-97	159.700	6.42	121684	328688	790.82
Mar-97	159.800	6.69	122000	318550	757.12
Apr-97	159.900	6.89	122293	323938	801.34
May-97	159.900	6.71	122551	326600	848.28
Jun-97	160.200	6.49	122818	324500	885.14
Jul-97	160.400	6.22	123131	325563	954.31
Aug-97	160.800	6.30	123092	322950	899.47
Sep-97	161.200	6.21	123604	321125	947.28
Oct-97	161.500	6.03	123945	312500	914.62
Nov-97	161.700	5.88	124251	312700	955.4
Dec-97	161.800	5.81	124554	316063	970.43
Jan-98	162.000	5.54	124830	318800	980.28
Feb-98	162.000	5.57	125026	317375	1049.34

Date	CPI	RTS	TNP	JCF	SP500
Mar-98	162.000	5.65	125177	316813	1101.75
Apr-98	162.200	5.64	125456	312625	1111.75
May-98	162.600	5.65	125862	309800	1090.82
Jun-98	162.800	5.50	126080	322500	1133.84
Jul-98	163.200	5.46	126204	345000	1120.67
Aug-98	163.400	5.34	126551	318250	957.28
Sep-98	163.500	4.81	126775	306875	1017.01
Oct-98	163.900	4.53	126971	307400	1098.67
Nov-98	164.100	4.83	127254	315250	1163.63
Dec-98	164.400	4.65	127601	313813	1229.23
Jan-99	164.700	4.72	127726	327750	1279.64
Feb-99	164.700	5.00	128137	305063	1238.33
Mar-99	164.800	5.23	128244	303188	1286.37
Apr-99	165.900	5.18	128619	308000	1335.18
May-99	166.000	5.54	128831	302300	1301.84
Jun-99	166.000	5.90	129092	297688	1372.71
Jul-99	166.700	5.79	129411	294300	1328.72
Aug-99	167.100	5.94	129578	296188	1320.41
Sep-99	167.800	5.92	129791	287813	1282.71
Oct-99	168.100	6.11	130192	293350	1362.93
Nov-99	168.400	6.03	130483	282063	1388.91
Dec-99	168.800	6.28	130778	281438	1469.25
Jan-00	169.300	6.66	131008	285300	1394.46
Feb-00	170.000	6.52	131138	294125	1366.42
Mar-00	171.000	6.26	131606	279625	1498.58
Apr-00	170.900	5.99	131893	269000	1452.43
May-00	171.200	6.44	132119	282500	1420.6
Jun-00	172.200	6.10	132074	285750	1454.6
Jul-00	172.700	6.05	132251	293150	1430.83
Aug-00	172.700	5.83	132237	307125	1517.68
Sep-00	173.600	5.80	132371	306400	1436.51
Oct-00	173.900	5.74	132357	299188	1429.4
Nov-00	174.200	5.72	132582	318125	1314.95
Dec-00	174.600	5.24	132724	341450	1320.28
1-Jan	175.600	5.16	132694	343188	1366.01
1-Feb	176.000	5.10	132766	361938	1239.94
1-Mar	176.100	4.89	132741	383500	1160.33
1-Apr	176.400	5.14	132460	391250	1249.46
1-May	177.300	5.39	132422	394000	1255.82
1-Jun	177.700	5.28	132293	400750	1224.38
1-Jul	177.400	5.24	132178	396313	1211.23

Date	CPI	RTS	TNP	JCF	SP500
1-Aug	177.400	4.97	132020	396875	1133.58
1-Sep	178.100	4.73	131778	411550	1040.94
1-Oct	177.600	4.57	131454	478063	1059.78
1-Nov	177.500	4.65	131160	455750	1139.45
1-Dec	177.400	5.09	130989	430750	1148.08
2-Jan	177.700	5.04	130847	409375	1130.2
2-Feb	178.000	4.91	130714	404313	1106.73
2-Mar	178.500	5.28	130695	401700	1147.39
2-Apr	179.300	5.21	130615	438188	1076.92
2-May	179.500	5.16	130607	413500	1067.14
2-Jun	179.600	4.93	130664	392900	989.82
2-Jul	180.000	4.65	130579	387125	911.62
2-Aug	180.500	4.26	130564	390350	916.07
2-Sep	180.800	3.87	130504	405500	815.28
2-Oct	181.200	3.94	130629	406563	885.76
2-Nov	181.500	4.05	130639	400000	936.31
2-Dec	181.800	4.03	130481	405250	879.82
3-Jan	182.600	4.05	130575	397563	855.7
3-Feb	183.600	3.90	130422	405375	841.15
3-Mar	183.900	3.81	130212	424050	848.18
3-Apr	183.200	3.96	130167	429625	916.92
3-May	182.900	3.57	130156	429500	963.59
3-Jun	183.100	3.33	130166	423750	974.5
3-Jul	183.700	3.98	130189	418500	990.31
3-Aug	184.500	4.45	130148	400750	1008.01
3-Sep	185.100	4.27	130250	401000	995.97
3-Oct	184.900	4.29	130446	383625	1050.71
3-Nov	185.000	4.30	130462	369900	1058.2
3-Dec	185.500	4.27	130586	360188	1111.92
4-Jan	186.300	4.15	130747	356300	1131.13
4-Feb	186.700	4.08	130791	365625	1144.94
4-Mar	187.100	3.83	131123	346250	1126.21
4-Apr	187.400	4.35	131372	345125	1107.3
4-May	188.200	4.72	131679	339000	1120.68
4-Jun	188.900	4.73	131753	346063	1140.84
4-Jul	189.100	4.50	131785	343850	1101.72
4-Aug	189.200	4.28	131917	340750	1104.24
4-Sep	189.800	4.13	132079	337750	1114.58
4-Oct	190.800	4.10	132425	337350	1130.2
4-Nov	191.700	4.19	132490	330688	1173.82
4-Dec	191.700	4.23	132619	328250	1211.92

Date	CPI	RTS	TNP	JCF	SP500
5-Jan	191.600	4.22	132753	340250	1181.27
5-Feb	192.400	4.17	132992	317813	1203.6
5-Mar	193.100	4.50	133126	324375	1180.59
5-Apr	193.700	4.34	133489	326450	1156.85
5-May	193.600	4.14	133664	324625	1191.5
5-Jun	193.700	4.00	133909	330313	1191.33
5-Jul	194.900	4.18	134282	324450	1234.18
5-Aug	196.100	4.26	134478	316000	1220.33
5-Sep	198.800	4.20	134545	355000	1228.81
5-Oct	199.100	4.46	134629	371450	1207.01
5-Nov	198.100	4.54	134966	321750	1249.48
5-Dec	198.100	4.47	135125	318000	1248.29
6-Jan	199.300	4.42	135402	304938	1280.08
6-Feb	199.400	4.57	135717	288750	1280.66
6-Mar	199.700	4.72	135997	298313	1294.87
6-Apr	200.700	4.99	136179	299600	1310.61
6-May	201.300	5.11	136202	327438	1270.09
6-Jun	201.800	5.11	136279	313125	1270.2
6-Jul	202.900	5.09	136486	317700	1276.66
6-Aug	203.800	4.88	136670	313063	1303.82
6-Sep	202.800	4.72	136827	315850	1335.85
6-Oct	201.900	4.73	136829	313875	1377.94
6-Nov	202.000	4.60	137039	320313	1400.63
6-Dec	203.100	4.56	137210	325150	1418.3
7-Jan	203.437	4.76	137448	323313	1438.24
7-Feb	204.226	4.72	137536	319250	1406.82
7-Mar	205.288	4.56	137724	314900	1420.86
7-Apr	205.904	4.69	137802	318000	1482.37
7-May	206.755	4.75	137946	305813	1530.62
7-Jun	207.234	5.10	138017	312700	1503.35
7-Jul	207.603	5.00	137984	316063	1455.27
7-Aug	207.667	4.67	137968	314188	1473.99
7-Sep	208.547	4.52	138053	317250	1526.75
7-Oct	209.190	4.53	138135	320813	1549.38
7-Nov	210.834	4.15	138253	331875	1481.14
7-Dec	211.445	4.10	138350	343850	1468.36
8-Jan	212.174	3.74	138365	343625	1378.55
8-Feb	212.687	3.74	138279	345375	1330.63
8-Mar	213.448	3.51	138199	354300	1322.7
8-Apr	213.942	3.68	137985	365313	1385.59
8-May	215.208	3.88	137803	365900	1400.38

Date	CPI	RTS	TNP	JCF	SP500
8-Jun	217.463	4.10	137631	375438	1280
8-Jul	219.016	4.01	137421	387063	1267.38
8-Aug	218.690	3.89	137162	427950	1282.83
8-Sep	218.877	3.69	136710	447000	1166.36
8-Oct	216.995	3.81	136236	475688	968.75
8-Nov	213.153	3.53	135471	503300	896.24
8-Dec	211.398	2.42	134774	554500	903.25
9-Jan	211.933	2.52	133976	556450	825.88
9-Feb	212.705	2.87	133275	628500	735.09
9-Mar	212.495	2.82	132449	654875	797.87
9-Apr	212.709	2.93	131765	642188	872.81
9-May	213.022	3.29	131411	616200	919.14
9-Jun	214.790	3.72	130944	602000	919.32
9-Jul	214.726	3.56	130617	576875	987.48
9-Aug	215.445	3.59	130401	561850	1020.62
9-Sep	215.861	3.40	130174	553625	1057.08
9-Oct	216.509	3.39	129976	531350	1036.19
9-Nov	217.234	3.40	129970	510313	1095.63
9-Dec	217.347	3.59	129687	487750	1115.1
10-Jan	217.466	3.73	129705	478500	1073.87
10-Feb	217.251	3.69	129655	483625	1104.49
10-Mar	217.305	3.73	129811	477438	1169.43
10-Apr	217.376	3.85	130062	468438	1186.69
10-May	217.299	3.42	130578	457900	1089.41
10-Jun	217.285	3.20	130456	460125	1030.71
10-Jul	217.677	3.01	130395	455450	1101.6
10-Aug	218.012	2.70	130353	474875	1049.33
10-Sep	218.281	2.65	130296	459063	1141.2
10-Oct	219.024	2.54	130537	449900	1183.26
10-Nov	219.544	2.76	130674	435563	1180.55
10-Dec	220.437	3.29	130745	426563	1257.64
11-Jan	221.082	3.39	130815	426250	1286.12
11-Feb	221.816	3.58	130983	415938	1327.22
11-Mar	222.955	3.41	131195	403938	1325.83
11-Apr	224.056	3.46	131517	407850	1363.61
11-May	224.918	3.17	131619	429688	1345.2
11-Jun	224.990	3.00	131836	418125	1320.64
11-Jul	225.553	3.00	131942	413900	1292.28
11-Aug	226.149	2.30	132064	407625	1218.89
11-Sep	226.674	1.98	132285	415938	1131.42
11-Oct	226.761	2.15	132468	404200	1253.3

Date	CPI	RTS	TNP	JCF	SP500
11-Nov	227.136	2.01	132632	392375	1246.96
11-Dec	227.093	1.98	132828	382650	1257.6
12-Jan	227.666	1.97	133188	383188	1312.41
12-Feb	228.138	1.97	133414	368938	1365.68
12-Mar	228.732	2.17	133657	367050	1408.47
12-Apr	229.184	2.05	133753	372813	1397.91
12-May	228.884	1.80	133863	373625	1310.33
12-Jun	228.825	1.62	133951	378450	1362.16
12-Jul	228.779	1.53	134111	371813	1379.32
12-Aug	229.952	1.68	134261	371000	1406.58
12-Sep	231.086	1.72	134422	380350	1440.67
12-Oct	231.652	1.75	134647	367063	1412.16
12-Nov	231.190	1.65	134850	388438	1416.18
12-Dec	231.099	1.72	135064	375050	1426.19
13-Jan	231.321	1.91	135261	362875	1498.11
13-Feb	232.599	1.98	135541	355000	1514.68
13-Mar	232.075	1.96	135682	347250	1569.19
13-Apr	231.707	1.76	135885	352813	1597.57
13-May	232.124	1.93	136084	341625	1630.74
13-Jun	232.860	2.30	136285	345950	1606.28
13-Jul	233.252	2.58	136434	345125	1685.73
13-Aug	233.433	2.74	136636	334700	1632.97
13-Sep	233.743	2.81	136800	320375	1681.55
13-Oct	233.782	2.62	137037	341063	1756.54
13-Nov	234.033	2.72	137311	339000	1805.81
13-Dec	234.594	2.90	137395	343063	1848.36
14-Jan	234.933	2.86	137539	338125	1782.59
14-Feb	235.169	2.71	137761	336500	1859.45
14-Mar	235.640	2.72	137964	327650	1872.34
14-Apr	236.254	2.71	138268	316438	1883.95
14-May	237.083	2.56	138497	318900	1923.57
14-Jun	237.693	2.60	138764	314375	1960.23

Appendix B: Output Data and Forecast Results

All train and validation data are combined in one table but validation data are bold and italic in the table.

	Predicted			Actual
Date	MRL	ANN	SVR	Y
Mar-93	6.8	6.7	6.9	7.0
Apr-93	6.7	6.6	7.0	7.1
May-93	7.0	6.9	7.0	7.1
Jun-93	7.0	6.9	6.9	7.0
Jul-93	***6.8***	***6.8***	***6.9***	***6.9***
Aug-93	6.8	6.7	6.9	6.8
Sep-93	6.7	6.7	6.8	6.7
Oct-93	6.9	6.8	6.8	6.8
Nov-93	6.7	6.6	6.7	6.6
Dec-93	***6.8***	***6.7***	***6.6***	***6.5***
Jan-94	6.7	6.6	6.6	6.6
Feb-94	6.4	6.4	6.6	6.6
Mar-94	6.5	6.4	6.5	6.5
Apr-94	6.7	6.6	6.4	6.4
May-94	***6.3***	***6.2***	***6.3***	***6.1***
Jun-94	6.1	6.0	6.1	6.1
Jul-94	6.2	6.1	6.0	6.1
Aug-94	6.1	6.0	6.0	6.0
Sep-94	6.0	5.9	5.9	5.9
Oct-94	***5.9***	***5.8***	***5.8***	***5.8***
Nov-94	5.8	5.7	5.8	5.6
Dec-94	5.7	5.6	5.7	5.5
Jan-95	5.5	5.4	5.6	5.6
Feb-95	5.5	5.4	5.6	5.4
Mar-95	***5.5***	***5.4***	***5.6***	***5.4***
Apr-95	5.5	5.4	5.6	5.8
May-95	5.6	5.5	5.6	5.6
Jun-95	5.7	5.6	5.6	5.6
Jul-95	6.0	5.9	5.7	5.7
Aug-95	***6.1***	***6.0***	***5.7***	***5.7***
Sep-95	6.1	6.0	5.7	5.6
Oct-95	5.9	5.8	5.6	5.5
Nov-95	5.9	5.9	5.6	5.6
Dec-95	6.0	5.9	5.6	5.6

	Predicted			Actual
Date	MRL	ANN	SVR	Y
Jan-96	***6.1***	***6.0***	***5.6***	***5.6***
Feb-96	6.0	6.0	5.6	5.5
Mar-96	6.1	6.0	5.5	5.5
Apr-96	6.2	6.1	5.6	5.6
May-96	6.0	6.0	5.6	5.6
Jun-96	***6.0***	***5.9***	***5.6***	***5.3***
Jul-96	5.6	5.5	5.4	5.5
Aug-96	5.5	5.4	5.4	5.1
Sep-96	5.4	5.3	5.4	5.2
Oct-96	5.3	5.2	5.3	5.2
Nov-96	***5.3***	***5.3***	***5.3***	***5.4***
Dec-96	5.4	5.3	5.3	5.4
Jan-97	5.4	5.3	5.2	5.3
Feb-97	5.5	5.4	5.3	5.2
Mar-97	5.4	5.3	5.3	5.2
Apr-97	***5.2***	***5.1***	***5.1***	***5.1***
May-97	4.9	4.9	5.1	4.9
Jun-97	4.9	4.9	5.1	5.0
Jul-97	5.0	4.9	5.0	4.9
Aug-97	4.9	4.9	4.9	4.8
Sep-97	***5.0***	***4.9***	***4.8***	***4.9***
Oct-97	4.9	4.9	4.9	4.7
Nov-97	4.9	4.8	4.8	4.6
Dec-97	4.7	4.7	4.7	4.7
Jan-98	4.7	4.7	4.6	4.6
Feb-98	***4.7***	***4.7***	***4.6***	***4.6***
Mar-98	4.7	4.7	4.6	4.7
Apr-98	4.7	4.7	4.5	4.3
May-98	4.7	4.6	4.5	4.4
Jun-98	4.6	4.6	4.4	4.5
Jul-98	***4.4***	***4.4***	***4.4***	***4.5***
Aug-98	4.6	4.6	4.5	4.5
Sep-98	4.9	4.8	4.7	4.6
Oct-98	4.4	4.4	4.6	4.5
Nov-98	4.3	4.4	4.5	4.4
Dec-98	***4.4***	***4.4***	***4.5***	***4.4***
Jan-99	4.4	4.4	4.4	4.3
Feb-99	4.4	4.4	4.5	4.4
Mar-99	4.6	4.5	4.5	4.2
Apr-99	4.2	4.2	4.3	4.3

	Predicted			Actual
Date	MRL	ANN	SVR	Y
May-99	***4.1***	***4.2***	***4.3***	***4.2***
Jun-99	4.2	4.3	4.3	4.3
Jul-99	4.0	4.2	4.2	4.3
Aug-99	3.9	4.1	4.1	4.2
Sep-99	3.8	4.0	4.1	4.2
Oct-99	***3.8***	***4.0***	***4.1***	***4.1***
Nov-99	3.7	3.9	4.1	4.1
Dec-99	3.7	4.0	4.1	4.0
Jan-00	3.6	3.9	4.1	4.0
Feb-00	3.5	3.9	4.1	4.1
Mar-00	***3.4***	***3.8***	***4.1***	***4.0***
Apr-00	3.6	3.9	4.1	3.8
May-00	3.5	3.8	4.1	4.0
Jun-00	3.3	3.7	4.1	4.0
Jul-00	3.3	3.7	4.0	4.0
Aug-00	***3.5***	***3.8***	***4.0***	***4.1***
Sep-00	3.6	3.9	3.9	3.9
Oct-00	3.8	4.0	3.9	3.9
Nov-00	3.8	4.0	3.9	3.9
Dec-00	3.7	3.9	3.9	3.9
Jan-01	***3.8***	***4.0***	***4.0***	***4.2***
Feb-01	4.2	4.2	4.1	4.2
Mar-01	4.3	4.3	4.2	4.3
Apr-01	4.4	4.4	4.5	4.4
May-01	4.7	4.5	4.8	4.3
Jun-01	***4.8***	***4.6***	***4.8***	***4.5***
Jul-01	4.9	4.7	4.9	4.6
Aug-01	5.1	4.8	5.0	4.9
Sep-01	5.0	4.8	5.0	5.0
Oct-01	5.1	4.9	5.1	5.3
Nov-01	***5.3***	***5.1***	***5.4***	***5.5***
Dec-01	6.2	5.7	5.8	5.7
Jan-02	6.0	5.6	5.7	5.7
Feb-02	5.7	5.4	5.6	5.7
Mar-02	5.5	5.3	5.5	5.7
Apr-02	***5.4***	***5.3***	***5.4***	***5.9***
May-02	5.5	5.3	5.5	5.8
Jun-02	5.9	5.7	5.9	5.8
Jul-02	5.6	5.5	5.7	5.8
Aug-02	5.4	5.3	5.6	5.7

	Predicted			Actual
Date	MRL	ANN	SVR	Y
Sep-02	***5.3***	***5.3***	***5.7***	***5.7***
Oct-02	5.4	5.5	5.7	5.7
Nov-02	5.6	5.8	5.9	5.9
Dec-02	5.7	5.7	5.8	6.0
Jan-03	5.6	5.7	5.7	5.8
Feb-03	***5.7***	***5.8***	***5.8***	***5.9***
Mar-03	5.6	5.8	5.9	5.9
Apr-03	5.8	6.0	6.0	6.0
May-03	6.1	6.2	6.1	6.1
Jun-03	6.2	6.2	6.1	6.3
Jul-03	***6.2***	***6.2***	***6.0***	***6.2***
Aug-03	6.2	6.2	6.0	6.1
Sep-03	6.1	6.1	6.0	6.1
Oct-03	5.9	6.0	6.0	6.0
Nov-03	6.0	6.0	6.0	5.8
Dec-03	***5.7***	***5.7***	***5.8***	***5.7***
Jan-04	5.6	5.6	5.7	5.7
Feb-04	5.5	5.6	5.6	5.6
Mar-04	5.5	5.5	5.6	5.8
Apr-04	5.6	5.6	5.7	5.6
May-04	***5.4***	***5.4***	***5.6***	***5.6***
Jun-04	5.3	5.3	5.4	5.6
Jul-04	5.1	5.2	5.3	5.5
Aug-04	5.2	5.3	5.3	5.4
Sep-04	5.2	5.3	5.4	5.4
Oct-04	***5.2***	***5.3***	***5.4***	***5.5***
Nov-04	5.2	5.3	5.4	5.4
Dec-04	5.2	5.3	5.4	5.4
Jan-05	5.1	5.2	5.3	5.3
Feb-05	5.1	5.2	5.3	5.4
Mar-05	***5.2***	***5.2***	***5.2***	***5.2***
Apr-05	4.9	5.1	5.2	5.2
May-05	5.0	5.1	5.1	5.1
Jun-05	5.0	5.1	5.1	5.0
Jul-05	4.9	5.0	5.1	5.0
Aug-05	***4.9***	***5.0***	***5.0***	***4.9***
Sep-05	4.9	4.9	4.9	5.0
Oct-05	4.8	4.9	4.9	5.0
Nov-05	5.4	5.4	5.2	5.0
Dec-05	5.6	5.5	5.2	4.9

	Predicted			Actual
Date	MRL	ANN	SVR	Y
Jan-06	***4.8***	***4.9***	***4.7***	***4.7***
Feb-06	4.8	4.9	4.7	4.8
Mar-06	4.7	4.8	4.8	4.7
Apr-06	4.4	4.6	4.7	4.7
May-06	4.5	4.6	4.6	4.6
Jun-06	***4.4***	***4.6***	***4.5***	***4.6***
Jul-06	4.8	4.8	4.5	4.7
Aug-06	4.6	4.7	4.6	4.7
Sep-06	4.7	4.8	4.6	4.5
Oct-06	4.7	4.8	4.6	4.4
Nov-06	***4.6***	***4.7***	***4.5***	***4.5***
Dec-06	4.6	4.6	4.5	4.4
Jan-07	4.7	4.6	4.5	4.6
Feb-07	4.8	4.7	4.5	4.5
Mar-07	4.7	4.6	4.5	4.4
Apr-07	***4.6***	***4.6***	***4.4***	***4.5***
May-07	4.7	4.6	4.5	4.4
Jun-07	4.8	4.7	4.6	4.6
Jul-07	4.7	4.6	4.7	4.7
Aug-07	4.7	4.6	4.7	4.6
Sep-07	***4.7***	***4.6***	***4.6***	***4.7***
Oct-07	4.8	4.7	4.7	4.7
Nov-07	4.9	4.7	4.9	4.7
Dec-07	5.0	4.8	4.9	5.0
Jan-08	5.2	4.9	5.0	5.0
Feb-08	***5.3***	***5.0***	***5.0***	***4.9***
Mar-08	5.4	5.1	5.1	5.1
Apr-08	5.4	5.2	5.1	5.0
May-08	5.6	5.3	5.3	5.4
Jun-08	5.8	5.5	5.5	5.6
Jul-08	***5.9***	***5.5***	***5.5***	***5.8***
Aug-08	6.1	5.9	5.7	6.1
Sep-08	6.4	6.2	6.0	6.1
Oct-08	6.9	6.6	6.6	6.5
Nov-08	7.2	7.0	7.0	6.8
Dec-08	***7.4***	***7.3***	***7.3***	***7.3***
Jan-09	7.7	7.6	7.8	7.8
Feb-09	8.5	8.0	8.5	8.3
Mar-09	8.7	8.4	8.7	8.7
Apr-09	9.6	9.2	9.1	9.0

	Predicted			Actual
Date	MRL	ANN	SVR	Y
May-09	***10.1***	***9.6***	***9.1***	***9.4***
Jun-09	10.2	9.8	9.3	9.5
Jul-09	10.0	9.8	9.6	9.5
Aug-09	10.0	10.0	9.7	9.6
Sep-09	9.8	9.9	9.8	9.8
Oct-09	***9.7***	***9.9***	***9.8***	***10.0***
Nov-09	9.8	9.9	9.9	9.9
Dec-09	9.6	9.9	9.9	9.9
Jan-10	9.4	9.8	9.9	9.7
Feb-10	9.2	9.7	9.8	9.8
Mar-10	***9.0***	***9.6***	***9.6***	***9.9***
Apr-10	9.1	9.7	9.7	9.9
May-10	9.1	9.5	9.6	9.6
Jun-10	8.9	9.3	9.4	9.4
Jul-10	8.6	9.2	9.3	9.5
Aug-10	***8.7***	***9.2***	***9.3***	***9.5***
Sep-10	8.7	9.2	9.4	9.5
Oct-10	9.0	9.5	9.5	9.5
Nov-10	8.9	9.3	9.4	9.8
Dec-10	8.8	9.2	9.3	9.4
Jan-11	***8.6***	***9.0***	***9.2***	***9.1***
Feb-11	8.5	9.0	9.2	9.0
Mar-11	8.6	9.0	9.2	9.0
Apr-11	8.5	8.9	9.0	9.1
May-11	8.4	8.8	9.0	9.0
Jun-11	***8.4***	***8.7***	***8.9***	***9.1***
Jul-11	8.7	9.0	9.2	9.0
Aug-11	8.5	8.9	9.0	9.0
Sep-11	8.5	8.9	9.0	9.0
Oct-11	8.5	8.9	8.8	8.8
Nov-11	***8.5***	***8.9***	***8.5***	***8.6***
Dec-11	8.4	8.7	8.6	8.5
Jan-12	8.3	8.6	8.4	8.2
Feb-12	8.1	8.5	8.3	8.3
Mar-12	8.1	8.3	8.3	8.2
Apr-12	***7.9***	***8.1***	***8.1***	***8.2***
May-12	7.9	8.1	8.1	8.2
Jun-12	8.0	8.1	8.1	8.2
Jul-12	7.9	8.1	8.0	8.2
Aug-12	8.0	8.1	7.9	8.1

	Predicted			Actual
Date	MRL	ANN	SVR	Y
Sep-12	***7.9***	***7.9***	***7.8***	***7.8***
Oct-12	7.9	8.0	7.9	7.8
Nov-12	8.1	8.1	7.9	7.8
Dec-12	7.9	7.9	7.8	7.9
Jan-13	8.1	8.0	7.8	7.9
Feb-13	***7.9***	***7.7***	***7.7***	***7.7***
Mar-13	7.7	7.6	7.6	7.5
Apr-13	7.7	7.5	7.6	7.5
May-13	7.5	7.3	7.4	7.5
Jun-13	7.6	7.3	7.3	7.5
Jul-13	***7.4***	***7.1***	***7.2***	***7.3***
Aug-13	7.4	7.2	7.3	7.2
Sep-13	7.4	7.1	7.1	7.2
Oct-13	7.2	7.0	7.1	7.2
Nov-13	7.0	6.8	6.9	7.0
Dec-13	***7.3***	***6.8***	***6.8***	***6.7***
Jan-14	7.2	6.7	6.6	6.6
Feb-14	7.3	6.8	6.5	6.7
Mar-14	7.2	6.8	6.6	6.7
Apr-14	7.2	6.6	6.4	6.3
May-14	***7.1***	***6.5***	***6.3***	***6.3***
Jun-14	6.9	6.4	6.2	6.1
Jul-14	7.0	6.4	6.1	6.2
Aug-14	6.9	6.3	6.0	6.1